Production-Driven Patch Generation and Validation

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Abstract—We present an original concept for patch generation in production. Our idea is to generate patches on-the-fly based on automated failure oracles (such as exceptions), and then to perform live regression testing in production. The latter is achieved by feeding a sandboxed version of the application with a copy of the production traffic, the “shadow traffic”.

I. INTRODUCTION

One of the most common problem statement of automatic software repair is that, given a failing test case and a regression test suite, synthesize a patch that makes the failing test pass while satisfying the regression suite. This is both a well-formed and a reasonable problem statement, because it fits with the kind of tests that are used in practice such as xUnit tests.

However, requiring the presence of a failing test case and a regression test suite can also be considered as an unreasonable requirement. First, because it is a time-consuming activity for developers to translate a reported issue into a failing test case. Second, it has recently been shown that the state-of-the-art of patch generation techniques is very sensitive to flaws in the regression tests [1]–[3]. If the regression test suite misses one or more cases, the generated patches are often incorrect.

In this paper, our motivation is to perform patch generation with weaker requirements (failure reproduction with a failing test case and good regression tests). We aim at having the benefits of automatically generated patches without paying the price of reproducing field bugs in test cases and maintaining high-quality regression tests. Achieving this would greatly expand the applicability of automatic repair and likely yield a bigger impact on industrial practice.

This paper exposes our solution to this problem. Our contribution is an architecture, called BikiniRepair, which is “testless” : it generates patches requiring neither a failing test case nor a regression test suite. The key idea of BikiniRepair is to perform regression testing directly on production data. The process of BikiniRepair is as follows. First, BikiniRepair uses production assertions or exceptions to detect failures; the current implementation focuses on null dereferences – the #1 crashing exception in production [4]. Second, right after the failure is detected in production, a patch is searched in a sandboxed environment that mimics the production one. If one exists, it fixes the failure. Third, the patches are tested for regression, directly in production, based on traffic that is an exact copy of the production traffic – we call it shadow traffic. The regression test is also done in a sandboxed environment. The key novel aspect of our approach is to perform live regression testing in production using multi-version execution.

BikiniRepair has been realized in a prototype implementation for Java which focuses on generating source code patches for null dereferences.

The evaluation of BikiniRepair is challenging. It requires real-world reproducible bugs in a production-like environment (and not simply test cases as usually done in offline patch generation research). It also requires production traffic for the application under consideration. This second point means that evaluating research contributions on automatic repair in production is much harder that evaluating research contributions on off-line patch generation techniques. Consequently, the evaluation we report in this paper is made of two qualitative case studies. Those two case studies are about real field bugs in large open-source e-commerce applications, Mayocat and Broadleaf Commerce. They show that our prototype implementation is able to generate source code patches directly in production. This is a first validation of the BikiniRepair concept.

This is a new line of research in automatic repair. Compared to classical test-suite based patch generation (e.g. [5]), BikiniRepair does patch generation online, i.e. as soon as the failure happens, with no need for reproducing the failure, at runtime. Yet, BikiniRepair is not a runtime repair technique either (e.g. [6]): while the patches are generated online, they are applied later, once the developer has validated them.

To sum up, our contributions are:

• BikiniRepair, an architecture for patch generation that performs live regression testing in production using multi-version execution. It requires neither a failing test case, nor a regression test suite.
• The use of shadow production systems and shadow traffic in the context of automatic repair to generate patches in production.
• The design and implementation of a Java implementation of this vision. It uses Docker for achieving sandboxing.
• Two case studies on real field bugs in large 2 open-source e-commerce applications, Mayocat and Broadleaf Commerce.

The remainder of this paper is as follows. Section II presents the current challenges of patch synthesis. Section III presents BikiniRepair. Section IV presents a qualitative evaluation of BikiniRepair. Section V presents the related works and Section VI concludes.
II. CHALLENGES OF PATCH GENERATION

Patch generation is one kind of automatic software repair technique [7], which consists of synthesizing source code level patches that repair certain bugs. Patch generation systems may use different oracles for driving the patch search, such as pre- and post-conditions (e.g. [8]), formal specifications (e.g. [9]), or test suites. The latter refers to test-suite based software repair, and has been proved to be a fruitful line of research, with systems such as GenProg [5], Semfix [10], Nopol [11], Prophet [12] to only name a few (for a comprehensive list, see [7]). The key advantage of test-suite based software repair is that it works with standard test suites, such as jUnit test suites in Java, hence is applicable to many industrial and open-source software applications. However, test-suite based repair suffers from two major problems, which we now discuss.

A. Problem #1: Cost of Reproducing Production Bugs

Test-suite based repair requires a failing test case. In this context, a failing test case contains two parts: the first part is a usage scenario that triggers the bug, the second part is an assertion encoding that specifies the expected behavior, typically an assertion on the program output which specifies the expected answer.

In production, end-users trigger bugs by exercising the system with inputs and sequences of interactions that were unforeseen by the development team. When this happens, they can report the bug to the development team through a support channel or a bug tracking system. The problem is that there is a major gap between an issue reported by an end-user and a failing test case that is usable by an automatic repair system. On the one hand, the problem is reported in a natural language and often its description is incomplete. On the other hand, we need a mechanically executable reproduction scenario and an automatically checkable assertion. With current patch generation systems, a developer is responsible for filling this gap, by manually analyzing the problem and translating the problem from natural language to a valid failing test case. Experienced developers know that reproducing production bugs can be extremely tedious and time consuming.\(^2\)

Our solution: BikiniRepair does patch generation on a runtime mirror of the production system so that the repair system has direct access to the production system state that triggers the failure at repair time.

B. Problem #2: Availability and Quality of Regression Tests

Finding a patch that makes a failing test case pass is relatively easy, for instance by returning an hard-coded value – the value that is expected in the failing assertion. This is obviously not a correct solution, and more generally, the problem is that a patch that fixes the failing test case may break some other functionality, i.e. the patch may introduce a regression. To overcome this problem, current test suite based repair systems use a regression test suite to discard invalid patches. In other words, the availability of a regression test suite is a mandatory requirement for using this kind of automatic repair techniques.

Recent research [1]–[3] has shown that the problem is not only the availability of a regression test suite, it is also a problem of quality. If the regression tests are too weak, many patches are incorrect, they fail to capture the essence of the bug (and hence its repair) and overfit to specific cases and values present in the tests. The proportion of incorrect overfitting patches is high, for instance, in a recent experiment on the Defects4j benchmark, the problem occurs 87% of the times [3]. This problem arises despite the availability of strong regression tests, resulting from disciplined and quality-focused development processes. To sum up, the availability and quality of regression tests bridles the effectiveness and impact of patch generation on industrial projects.

Our solution: BikiniRepair does regression validation on production traffic directly, so as to verify that the synthesized patch does not break anything, so that all behaviors actually used by end-users which worked before are kept functioning after patch application. The production traffic contains far more usage scenarios and diverse values than a regression test suite, this consequently reduces the risk of overfitting.

III. BIKINI REPAIR

We now present BikiniRepair, a novel software repair technique for generating patches without requiring failing test cases, directly in the production environment. BikiniRepair is a “testless” patch synthesis approach.

A. Intuition

The intuition behind BikiniRepair is twofold. First, one can use production runtime contracts to drive the generation of source code patches. This includes classical pre- and post-conditions and implicit contracts such that a accessed variable must not be null. The latter is important because the violations of those implicit contracts come for free in any modern runtime, usually under the form of runtime exceptions.\(^2\)

\(^2\)To our knowledge, there are unfortunately no academic empirical studies dedicated to this problem. However, this claim is supported by web posts describing such reproduction nightmares (e.g. https://frama.link/bs8KKeIcf), and by the fact that companies sell products to help reproduction and diagnosis (e.g. https://www.takipi.com)
The second intuition is that one can use the diversity of the production inputs to perform in-the-field regression testing on the synthesized patches. This has the advantage that the regression exactly corresponds to what actually matters.

B. Architecture

The BikiniRepair architecture is composed of seven components, as shown in Figure 1.

1) The Unmodified Application (see Section III-B1) is the application onto which automatic patch generation is plugged.
2) The Request Oracle Service (see Section III-B2) is a service that determines whether the application has successfully handled a request.
3) The Patch Synthesis Service (see Section III-B3) is the service that searches for patches that fix a given failure.
4) The Regression Assessment Service (see Section III-B4) performs regression testing on the generated patch. It applies the generated patches on the application and executes the request on it.
5) The Regression Oracle (see Section III-B5) is the component that validates the generated patches by comparing the original output of Unmodified Application to the output of the patched application for live production requests.
6) The Shadower (see Section III-B6) is used to duplicate the requests of the Unmodified Application. The duplicated requests are then sent in parallel to the Patch Synthesis Service and the Regression Assessment Service.
7) And the Patch Reporting Service (see Section III-B7) is the component that selects the best patches and communicates them to the developers.

Algorithm 1 shows the interactions between each component of the BikiniRepair. BikiniRepair receives the request from the client (line 1). Then it redirects the request to the Unmodified Application (line 2). Once the request has been handled by the Unmodified Application, the response is sent back to the client, yet it is additionally sent to the Request Oracle Service (arrow a in Figure 1) which verifies the viability of the output (line 4). If the Request Oracle Service determines that there is a failure, the request is sent to the Patch Synthesis Service (arrow b in Figure 1 and line 5). The patches generated by Patch Synthesis Service which pass the Request Oracle Service (i.e. fix the failure at hand) are sent to Regression Assessment Service (line 6). If the request has succeeded (no failure on the original application), the request is also sent to the Regression Assessment Service (line 8) where all the previously generated patches are being validated on-the-fly against the new request. When the Regression Assessment Service has identified valid patches with no regression, it sends them to the Patch Reporting Service.

To sum up, BikiniRepair does patch generation online, i.e. as soon as the failure happens, directly in production. However, while the patches are generated online, they are applied later, once the developer has validated them. The side effects of patch search or regression testing on the production state are completely sandboxed, with no interference with the production environment.

Algorithm 1 The main BikiniRepair algorithm

```
Input: A: the Unmodified Application
Input: G: the Patch Synthesis Service
Input: V: the Regression Assessment Service
Input: O: Request Oracle Service

1: while new request r_client from Client do
2:   output = A(r_client)
3:   send output to Client
4:   if O(output) is failure then
5:     patches = send r_client to G
6:     push patches to V
7:   else
8:     send r_client to V for regression (see Algorithm 2)
9:   end if
10: if ∃ validated patches ∈ V then
11:   p ← order the patches
12:   report p to developers
13: end if
14: end while
```

1) The Unmodified Application: BikiniRepair augments a production application with automatic patch generation capabilities. The requirement to deploy BikiniRepair is that the application must use requests, i.e. must have a message-driven architecture [13]. The type of request may vary between applications, for example a request in a web application will be the request sent by a user’s browser to a web-server, in a micro-service application, the request will typically a REST message, in a mobile application, a request would be a touch event triggered when a user touches a mobile device’s screen.

2) Request Oracle Service: The responsibility of the Request Oracle Service is to verify whether the application has succeeded to answer the request. For instance, in a web-server, the Request Oracle Service can check the HTTP request return code ("assert response_code != 500 (internal server error)") of check the presence or not of an exception. BikiniRepair works with generic oracles such as checking the absence of exceptions (e.g. in a web request container or in a thread monitor), and it can also work with domain-specific oracles written by software engineers on top of domain concepts and data (e.g. the returned XML must comply with a specific schema). When possible, the Request Oracle Service provide some information about the failure to help the Patch Synthesis Service to search for a patch. The information provided by default is the stack trace when the failure is based on an exception.

The BikiniRepair does not require a perfect Request Oracle Service, i.e. the Request Oracle Service may miss some failures (false negatives). In the case of false negatives, when the Request Oracle Service misses the failure detection, BikiniRepair simply does not generate patches: this is unfortunate but it impacts neither the original application nor the patches generated for the other failures. In the case of false positives, when the Request Oracle Service detects a failure when there
is no failure in reality, the Patch Synthesis Service would generate patches, yet they would be benign if they pass regression testing done by the Regression Assessment Service.

3) **Patch Synthesis Service:** The Patch Synthesis Service is the service that synthesizes patches that fix a failing request. BikiniRepair uses a template-based patch synthesis approach, presented later in Section III-C2 and Table I. An example of patch template for null dereference is adding a null check (“if (x!=null) x.m()”) around a statement that contains a field access or a method call. The patch templates are applied to the failure point, typically the line where an exception has occurred. In BikiniRepair, some templates are meta-templates which contain placeholders. The placeholders can be filled with elements from the context of the failure, for example to use an existing variable. For instance, in template “if (x!=null) return P”, P is a placeholder that can be instantiated with all type-compatible variables of the scope. For a given failure point, the Patch Synthesis Service performs an exhaustive application of all possible patch templates, together with an exhaustive search over the Cartesian product of all placeholders.

For each tentative patch, Patch Synthesis Service calls the Request Oracle Service (arrow c in Figure 1) to verify that the request has been correctly handled by the patch template under consideration (the failure has been fixed). Because the Patch Synthesis Service generates the patches only based on one request (the failing one), the patches may break the behavior of the application for other requests, in other word, the may introduce a regression. Thus, if the patch is successful on the failing request, the corresponding patch is transferred to the Regression Assessment Service (arrow d in Figure 1) that will further validates its correctness based on other requests.

The application and execution of candidate patches can change the state of the application in runtime. Consequently, each execution is done in a sandboxed environment, this nullifies the potential side effects of the request or of the patch templates. The sandboxed environment contains a shadow state of the application, which is regularly synchronized with the production one.

Since the space of patches is sometimes large, BikiniRepair uses a time budget. It explores the patch alternatives sequentially until they are all explored or until the time budget is consumed.

Beyond null dereferences, BikiniRepair can work with any patch model, whether domain-specific (for instance for out-of-bounds exception) or generic (à la Genprog [5]). If the patch model generates too much patches, i.e. the search space is too large, this would be a problem because it would represent a huge computation effort on the Patch Synthesis Service and much more importantly on the Regression Assessment Service.

4) **Regression Assessment Service:** The patches generated by the Patch Synthesis Service can introduce regressions because their generation only involves one request (the failing one). The Regression Assessment Service has the responsibly to check the behavior of the application when the generated patches are injected on other requests. It detects these regressions by comparing the output of the Unmodified Application against the output of the patch-augmented application. If the output is different, the patch is marked as invalid for the current request, because it has introduced a regression. This comparison is done on-the-fly, directly on production traffic. Doing regression testing “live” has the advantage that there is no need to record the potentially enormous amount of production data.

**Algorithm 2** is the main algorithm of the Regression Assessment Service. The Regression Assessment Service requires a copy of the Unmodified Application, the response of the Unmodified Application, a Regression Oracle (arrow e in Figure 1, presented below in Section III-B5), the Request Oracle Service and a list of patches to validate (previously sent by the Patch Synthesis Service). For each successful request (according to the Request Oracle Service) received from the Shadower (arrow f in Figure 1 and line 1 in Algorithm 2), the Regression Assessment Service iterates over each patch to detect regressions according to the regression oracle (line 3 in Algorithm 2). Finally, the information collected during regression testing on production traffic is sent to the Patch Reporting Service (arrow h in Figure 1).

5) **Regression Oracle:** The Regression Oracle compares the output of the Unmodified Application (arrow g in Figure 1) and the output of a patched version in the Regression Assessment Service for the same request. In BikiniRepair, the

If the outputs are different, the Regression Oracle marks the current patch as invalid. For example, a regression oracle for a web server compares the HTML text of both versions. The comparison is not necessarily a byte-to-byte one, it can include
heuristics to discard transient information such as time, cookie identifiers, etc.

6) Shadower: The role of the Shadower is to create shadow traffic from actual end-user traffic coming into the application. The “shadow traffic” is made of production requests that are duplicated one or several times and sent to sandboxed shadow applications. In our case, the shadow applications are the Patch Synthesis Service and Regression Assessment Service.

In BikiniRepair, the Shadower receives the requests from the clients duplicates them and sends one duplicate to each service of the architecture (arrows a, b, and f in Figure 1). The response is also shadowed for the regression oracle service (arrow g in Figure 1).

In the context of web applications, the concept of running multiple instances of an application is well known and heavily used: this is done for load balancing and rolling deployment. The difference between a load balancer and a Shadower is twofold: first, a load balancer does not duplicate the traffic; second, a load balancer does not send requests to sandboxed “sinks” as BikiniRepair does.

Since BikiniRepair is a production technique, it must have a reasonable impact on the performance of the application. In order to minimize the impact on the Unmodified Application, BikiniRepair computes the Regression Assessment Service and the Patch Synthesis Service asynchronously. Indeed, the goal of BikiniRepair is to perform patch generation, not automatic error recovery system. Hence, the Shadower directly sends the output as soon as the Unmodified Application has handled a request (even if there is a failure). BikiniRepair does not have to wait for the end of the patch search or the end regression testing for sending the response back to the client. The Shadower is thus the only component that impacts the performance of the Unmodified Application. However, since it mostly does request copying this is negligible (this will be evaluated in Section IV-E). In general, the impact on performance of the Shadower is similar to the one of web proxies and load balancers. If the Shadower is overwhelmed, i.e. the list of requests being handled asynchronously is too large, it does not shadow new requests.

7) Patch Reporting Service: The Patch Reporting Service is the service that communicates the results of BikiniRepair to the developers (arrow i in Figure 1).

It happens that multiple patches (corresponding to multiple patche templates) successfully pass the regression test over production traffic. Consequently the Patch Reporting Service has to sort the patches in order to first propose the most useful ones to the developers. To sort, the Patch Reporting Service uses the number of execution of the patched line in the Regression Assessment Service (the number of requests that execute the patch). The idea is that the more a patch has been executed by the Regression Assessment Service, the less likely it is to introduce a regression.

We now discuss the reporting medium to the human developer. There are several types of communication that can be used in the Patch Reporting Service. In the current prototype, we have a dashboard where the developers follow in real time the failures, the generated patches and the progression of the patch validation. We also imagine an approach integrated into the versioning system: the Patch Reporting Service can automatically create a pull request4 for the most likely patch identified to-date.

C. Prototype Implementation for Java

We have implemented a prototype of BikiniRepair for Java in a tool named Bikini4j. Bikini4j generates patches for null dereference failures. In total, Bikini4j is composed of 12 180 lines code.

1) Implementation of the Request Oracle Service: Bikini4j has a default request oracle based on exceptions. Any uncaught exception happening during the processing of a request is considered as a failure. In addition, for the case studies in the domain of web applications that is presented later in Section IV, we have also implemented a request oracle based on HTTP return codes. According to the specification of the HTTP status codes, the HTTP status code that begins with the digit “5” indicates that the server is aware that it has encountered an error. The Request Oracle Service checks that the HTTP status code begins with the digit “5” if it is the case the request is considering as failing otherwise as succeed.

2) Implementation of the Patch Synthesis Service: In our implementation, the Patch Synthesis Service is dedicated to null pointers and uses the technique from our previous work for searching the space of possible patches for null dereferences [14]. Table I presents our six patch templates, e.g. protecting the failing statement by a not-null check (if (x!=null) <stmt>). Four patch templates are meta templates, they are parametrized by an expression that creates or returns a valid object instead of the null value.

Sandboxing is achieved using Docker5, a major software containerization platform which provides powerful sandboxing (both disk and IO based) [15]: both the Patch Synthesis Service and the Regression Assessment Service are encapsulated in

4a proposition of code change, for instance on Github
5Docker website: https://www.docker.com/
their own Docker image. The persistent state is also duplicated
in two separate databases in their respective docker images, i.e.
the prototype implementation maintains a shadow state of the
production state.

3) Implementation of the Regression Assessment Service:
The Regression Assessment Service stores a list of patches
during regression testing. A Remote Method Invocation (RMI)
server is used to communicate the patches between the Patch
Synthesis Service and the Regression Assessment Service,
and from the Regression Assessment Service to the Patch
Reporting Service. The main advantage of RMI is that it runs
over TCP/IP and the TCP/IP traffic can cross the sandboxing
boundaries through port forwarding.

4) Implementation of the Regression Oracle: For the
Regression Oracle, we compare the body of the response of the
Unmodified Application against the output produced by the
patched application (e.g. the HTML body text). The compar-
ison can discard transient information (such as IP addresses)
using configurable, domain-specific heuristics. If the outputs
match, the patch is considered validated for the current request
otherwise the patch is permanently marked as invalid.

5) Implementation of the Shadower: The Shadower is im-
plemented with the Jetty Proxy Servlet. The major imple-
mentation challenge is to maintain a list of session identifiers
(e.g. cookies) for each shadowed service. When a session-
enabled request arrives with the session ID of the end-user’s
browser, it translates on the fly the session ID into the one
of the shadowed service (and vice-versa for the response).

6) Implementation of the Patch Reporting Service: The two
main components of the Patch Reporting Service are the patch
sorting component and the communication with the end-user.
The patch sorting component orders patches by the number
of executions of the patched lines, this information is sent
real-time by the Regression Assessment Service.

Bikini4j contains a web dashboard, where the developers
can access in real time the current patches of BikiniRepair:
the ones that have fixed at least one failure and the patch
that are under regression testing. For each patch, they can
visualize the number of failures of the system detected by
the Request Oracle Service, see the actual patch code, and the
patch validation metrics such as the number of executions done
by the Regression Assessment Service. With this dashboard,
the developers have a real-time view on the possible patches,
before taking the decision of integrating them into the main
branch of the code base.

IV. Evaluation

We now present the evaluation of BikiniRepair in order to
answer the main research question: is BikiniRepair able to
generate correct source code patches for real bugs, directly in
production with neither a failing test case nor a regression test
suite?

A. Challenges of Evaluation

Classical challenges. The empirical evaluation of automatic
repair systems can be done on seeded bugs or on real bugs that
happened in the field. In this paper, we aim at showing
the ability of BikiniRepair to repair real bugs from real
Java applications. Conducting an evaluation on real bugs is a
challenging project, the main challenges are: (C1) locate real
bug reports that are amenable to the repair technique under
study (for instance, for evaluating BikiniRepair, C1 requires
a null pointer exception in a client-server applications); (C2)
being able to compile and execute the exact version in which
the bug was present, for a codebase we are not familiar with;
(C3) being able to reproduce the bug, i.e. to have the input or
the sequence of interactions that triggers the bug; (C4) being
able to plug the automatic repair system in the application
under study (for instance, in BikiniRepair, this requires setting
up the sandboxing). As experienced by researchers working in
the field, this takes between several days and several weeks per
bug. Consequently, since our evaluation is mostly manual, it
involves a small number of bugs (as opposed to research where
the collection of evaluation data is partially automated).

Specific challenge. In BikiniRepair, there are one additional
challenge (C5) since we perform regression testing with pro-
duction traffic, an ideal evaluation would require a live or
recorded production traffic for the application under study.
This is extremely challenging to obtain because production
traffic contains privacy-sensitive information, and companies
are very careful with this. Consequently, we evaluate BikiniRe-
pair with simulated production traffic.

Comparative Evaluation. To our knowledge, there is no
patch generation technique in production to compare against.
We give in Section V a qualitative comparison against the
related work.

B. Experimental Protocol

To evaluate BikiniRepair, we set up the following experi-
mental protocol.

1) We identify an appropriate production application that
satisfies the inclusion criteria described in Section IV-C,
in particular, the application must contain a real null
dereference that we are able to reproduce.

2) We wrap the application in the BikiniRepair framework, in
particular, we create 3 docker images (recall that we use
docker for sandboxing): the first docker image contains the
Unmodified Application, the second docker image contains
a copy of the Unmodified Application augmented with the
Patch Synthesis Service, the third docker image contains
the Regression Assessment Service.

3) We configure the shadower for the application under con-
sideration, which means binding the requests and responses
to the docker images, and setting up the request oracle (e.g.
a check on the HTTP response code for a web application)

6Jetty Proxy Servlet http://www.eclipse.org/jetty/documentation/9.4.x/
proxy-servlet.html

7Should the reader know a way to obtain such production traffic, please
contact us.
4) Since we have no production traffic available (Challenge C5 discussed in Section IV-A) we set up a set of scripts to mimic a production environment and its traffic. One script inserts fake data in the application’s database (such as fake products and users in an e-commerce application). One script is responsible for automatically reproducing the failure-inducing request. The other scripts are responsible for exercising all relevant features of the application and detect potential regressions.

5) We launch the application and BikiniRepair, and we execute the scripts that emulate production traffic. This results in triggering a patch search by the Patch Synthesis Service and a regression assessment by the Regression Assessment Service.

For each application under consideration, this enables us to collect and to analyze: the “candidate patches” that are all the patches generated by the Patch Synthesis Service given a null dereference (they may pass or not the Request Oracle Service); the “request-oracle adequate patches” are the patches that pass the request oracle (and for which we do not know yet whether they introduce a regression); the “regression-oracle adequate patches” are the patches that pass both the request oracle and the regression oracle. Those patches are ready to be sent to the Patch Reporting Service and pushed to the developers.

Finally, a manual analysis step consists of identifying whether the human patch written by the developer for the failure under consideration has been found by BikiniRepair.

C. Selection of Cases

To select cases for the evaluation, we have to identify applications that meet the following criteria. First, the application must be a message-driven application (see Section III-B1). Second, it must be written in Java and one version must suffer from a null dereference bug, since our prototype implementation Bikini4j does patch search for null dereferences and is implemented in Java. Third, it must be open-source because we manipulate and generate source-level patches. Fourth, we must be able to reproduce the null dereference failure, given the information available in the bug report (affected version, crashing input, etc.).

We searched for such applications on the Github software repository with a focus on e-commerce applications, because e-commerce applications are typical web-based message driven applications present in our everyday life. For sake of open science and further research on this topic, this benchmark is made publicly available on GitHub, each bug being reproducible in a Docker image that considerably simplifies the failure triggering.\(^8\)

Eventually, we identify two applications that meet our criteria: Mayocat\(^9\) and BroadLeaf Commerce\(^10\). Both are e-commerce frameworks. Mayocat is composed of 31 231 lines of Java code, done over 1 670 commits and in development since 2012. BroadleafCommerce is bigger and older, it contains 154 309 lines of code, done over 9 779 commits and in development since 2008. For Mayocat, we consider bug Mayocat-231\(^11\). For BroadleafCommerce, we consider bug BroadleafCommerce-1282\(^12\).

D. Results

We now present the result of the evaluation of BikiniRepair on 2 real-world bugs in Java applications.

1) Case study of Mayocat-231:

a) Description of the bug: We now study the case of bug Mayocat-231 of the e-commerce application Mayocat. This bug is a null deference which happens when the website administrator selects a specific strategy to compute the shipping price of a cart. When the null dereference happens, the user is left with a white page. Worse, the user session (identified by a cookie and stored on the server side) becomes completely unusable, which means that the website is completely broken for this particular user. The client is thus unable to further navigate in the product list, buy a product or even click on the "contact the administrator" link to report the issue.

b) Human patch: Figure 2 shows the snippet of code written by the human developer to fix the bug Mayocat-231. The patch consist of using “BigDecimal.ZERO” when the shipping price per product (“carrier.getPerItem()”) is null. It is classical patch for null dereferences: a not-null check, here in the form of a ternary expression.

c) BikiniRepair patches: For this bug, the Patch Synthesis Service of BikiniRepair generates 288 candidate patches, all being compilable.\(^13\) They are instances of the 6 patch templates presented in Table I (recall that some templates

\(^8\)http://spirals-team.github.io/BikiniRepair-benchmark/
\(^9\)http://www.mayocat.org/
\(^10\)http://www.broadleafcommerce.com/
\(^11\)https://github.com/mayocat/mayocat-shop/issues/231
\(^12\)https://github.com/BroadleafCommerce/BroadleafCommerce/issues/1282
\(^13\)The complete list of BikiniRepair patches is available at http://spirals-team.github.io/BikiniRepair-benchmark/
Figure 4: A request-oracle adequate patch found by BikiniRepair for bug Mayocat-231.

are meta-templates that can be instantiated multiple times—such as “if not null, return new X”, where X is a valid constructor call). After application and execution, the Request Oracle Service discards 186 patches, i.e. they do not satisfy the request oracle for the failure inducing request. They are invalid because, even if they fix the initial null pointer exception, they produce another failure later in the execution. For example, let us consider Figure 3, which shows candidate patch that is invalidated by the request oracle. When this patch is applied, a null value is returned, which itself produces a new null dereference in the caller method. When this new dereference happens, the HTTP status of the request is set to “500”, interpreted by the Request Oracle Service as a failure. All the remaining 102 patches are sent to the Regression Assessment Service.

Let us now consider the Regression Assessment Service. In our simulation of bug Mayocat-231, the Regression Assessment Service does not reject any patch because of our simulated production traffic. For all inputs and sequences of events created in the simulated production traffic, the ones that execute the buggy line all produce a failure detected by the request oracle. This is due to the fact that the production traffic simulator is unable to create an input for this bug that requires regression testing (the bug report only provide us with crashing input). Note that this is a limitation of our production traffic generator, which is a very hard artifact to design, not a conceptual limitation of BikiniRepair.

Among the 102 patches synthesized by BikiniRepair which pass all oracles, none is syntactically equivalent to the patch written by the developer. However, one BikiniRepair patch, shown in Figure 4, is semantically equivalent, it has the same behaviour as the human patch. It replaces the null element (“carrier.getPerItem()”) by an existing variable “BigDecimal.ZERO” found in the execution context.

Our explanation of BikiniRepair generating a correct patch is that this patch is present in the search space of the patch model under consideration. A different patch model would not necessarily result in a correct patch, which would mean a limitation of the patch model, not a limitation of BikiniRepair. Furthermore, we have only analyzed a sample of patches, it may happen that another correct, yet slightly different patch may be found too. Indeed, Long and Rinard [16] have shown that many patch models have equivalently correct patches in their search space.

Regarding timing, it takes less than 5 minutes to generate the 288 candidate patches. Recall that the Patch Synthesis Service is called in an asynchronous manner by the shadower (see Section III-B6), which means that the end-user does not have to wait for those 5 minutes in front of the browser. For regression testing, the total time required is approx. the initial time for handling the request by the Unmodified Application (say ref) times the number of patches in the current list (list Q in Algorithm 2), under the assumption that no patch takes significantly more time than ref. However, this can be done in parallel, and if enough concurrent computing resources are available, this is in $O(1)$.

For real bug Mayocat-231, BikiniRepair generates source code patches, directly in production. Neither a manually written failure reproduction test nor a regression test suite is used. One of the generated patches is semantically equivalent to the patch written by the developer.

### 2) BroadleafCommerce-1282

We now study the case of bug BroadleafCommerce-1282, still in the domain of e-commerce. We focus on discussing two points that were not highlighted by the first case study.

a) **Description of the bug:** This bug is a null dereference that happens when the website administrator adds a customer with an email address that already exists in the database (i.e. that is already used by another customer). When this failure occurs, the user interface displays a dirty low level debugging stack trace. Contrary to bug Mayocat-231 which breaks the website, this bug has a lower severity.

Figure 5 shows the failure point, i.e. where the null deref-
future work on advanced patch models. It prevents interesting patches to be synthesized. This calls for repair techniques. This definitely simplifies the problem, but between the failure point is what is done in most runtime prototype implementation. Having a direct correspondence construction, as per the design of the patch model in our research, are in the same method as the failure point. This is by the application. 

BikiniRepair, the developer is always proposed to improve the email and/or in the request oracle results in improvable patches. In the absence of domain knowledge in the patch model, there are cases where the BikiniRepair patch silently skips the action to be done, with no feedback to the user. This shows that there are cases where the BikiniRepair patch handles the failure by exiting the method when utility method “findProperty” does not find the required property. With this patch, no dirty error message is displayed in the user interface.

c) Comparison against the Human Patch: When comparing BikiniRepair patches against the human patch, the surprise is that they are in different methods. The human patch, shown in Figure 6 is in method “validateUniqueUsername”, and it essentially replaces the error identifier “username” by “emailAddress”. Later on, at the failure point, the property that is looked-up (“emailAddress”) is found and no exception is thrown.

From the viewpoint of the request oracle (the absence of exception in this case study), both patches handled the failure and are correct. However, the human patch is conceptually better, because it transforms the exceptions into a clean and explicit warning about duplicate emails, while the BikiniRepair patch silently skips the action to be done, with no feedback to the user. This shows that there are cases where the absence of domain knowledge in the patch model and/or in the request oracle results in improvable patches. In BikiniRepair, the developer is always proposed to improve the synthesized patches before merging them in the code base of the application.

d) Discussion: As said earlier, the BikiniRepair patches are in the same method as the failure point. This is by construction, as per the design of the patch model in our prototype implementation. Having a direct correspondence between the failure point is what is done in most runtime repair techniques. This definitely simplifies the problem, but it prevents interesting patches to be synthesized. This calls for future work on advanced patch models.

For real bug BroadleafCommerce-1282, BikiniRepair generates a patch directly in production. However, it is a fully automated yet partial solution to the problem, because of lack of domain knowledge in the patch model or in the oracle. A BikiniRepair patch can be further improved by the developer before final acceptance.

E. Evaluation of Performance Impact of the Shadower

We now evaluate the impact of BikiniRepair on the performance of the application. As we have previously discussed in Section III-B6, the performance of the application is mostly impacted by the Shadower because the other services are executed asynchronously. In order to evaluate the performance of BikiniRepair, we execute 1000 sequential requests on the home page of the Mayocat application and then we execute the same 1000 requests on Mayocat but this time with the Shadower between the application and the client.

The result is as follows, it takes on average 0.104 second to make the request directly to Mayocat, and it takes on average 0.114 second to make the request through the Shadower (which copies the request, redirects the original request to the Mayocat application and copies the response of Mayocat to the oracles, Patch Synthesis Service and Regression Assessment Service. This represents a slowdown of 10.44%.

V. RELATED WORK

A. Patch Generation

The literature on patch generation based on test-suites is growing very fast. We only present a brief overview of notable contributions. GenProg by [5] applies genetic programming to the AST of a buggy program and generates patches by adding, deleting, or replacing AST nodes. Debroy and Wong [17] propose a mutation-based repair method inspired from mutation testing. This work combines fault localization with program mutation to exhaustively explore a space of possible patches. SemFix by [18] is a constraint based repair approach. It provides patches for assignments and conditions by combining symbolic execution and code synthesis. Nopol by [11], [19] is also a constraint based method, which focuses on repairing bugs in if-conditions and missing preconditions. DirectFix by [20] achieves the simplicity of patch generation with a Maximum Satisfiability (MaxSAT) solver to find the most concise patches. SPR [21] defines a set of staged repair operators so as to early discard many candidate repairs that cannot pass the supplied test suite and eventually to exhaustively explore a small and valuable search space.

BikiniRepair uses primarily uses a template-based patch generation approach. PAR by [22] uses 10 patch templates for common programming errors, Relifix [23] defines templates specifically for regression bugs. All of those approaches require a regression test suite to validate the patch, none of them leverage production traffic to assess the absence of regressions.

B. Runtime Repair in Production

There are several automatic repair techniques that handle failures in production. We now review the notables one and

```java
@@ FormBuilderServiceImpl.java
@@ -717,2 +717,5 @@
+ String idProperty = adminEntityService.getIdProperty((cmd);
+ if (entity.findProperty(idProperty) == null) {
+ return;
+ }
+ ef.setId(entity.findProperty(idProperty).getValue());
```
discuss whether they could be extended to generate source code patches.

Berger and Zorn [24] show that it is possible to effectively tolerate memory errors and avoid probabilistic memory safety by randomizing the memory allocation and providing memory replication. Since they consider the runtime infrastructure and not the application code, there is no direct patch generation strategy. Rx [25] is a runtime repair system based on changing the environment upon failures. Rx employs checkpoint-and-rollback for re-executing the buggy code when failures happen. Assure [26] is a self-healing system also based on checkpointing. In both cases, there is no patch generation strategy associated with the checkpoint and rollback mechanism.

Rinard et al. [6] present a technique called “failure oblivious computing” to avoid illegal memory accesses by adding additional code around each memory operation during the compilation process. For example, the additional code verifies at runtime that the program only uses the allocated memory. If the memory access is outside the allocated memory, the access is ignored instead crashing with a segmentation fault. One could extend failure oblivious computing by logging when the added code has been executed so as to propose it as a definitive source code patch to the developers.

Dobolyi and Weimer [27] present a technique to tolerate null dereferences. Using code transformation, they introduce hooks to inject manufactured values. This is also what has been done by Long et al. [28], which enrich this idea with the concept of “recovery shepherding” in a system called RCV. The key idea of recovery shepherding is to track the manufactured values so as to see 1) whether they are passed to system calls or files and 2) whether they disappear. Both approaches are not for patch generation, yet could be extended for. They do not try to validate the runtime change with oracles.

Carzaniga et al. [29] repair web applications at runtime with set of manually written, API-specific alternatives rules. This set can be seen as a hard-coded set of runtime patches. By using such a system in production, the number of successful applications of runtime patches is a natural ordering metric to recommend the most valuable to the developers for a permanent integration in the codebase.

Perkins et al. [30] propose ClearView, a system for automatically repairing errors in production. The system consists of monitoring the system execution on low-level registers to learn invariants. Those invariants are then monitored, and if a violation of an invariant is detected ClearView forces the restoration. ClearView could be extended to perform patch generation: it would mean reifying the learned invariants as a precondition. The main challenge would be to translate information learnt at the very low level of CPU register into predicates on variables in the source code.

C. Shadow Traffic

The concept of shadow traffic is related to the execution of multiple versions of the same software in parallel, called in the literature “multi-version execution” [31], “parallel execution” [32] or simply “dual execution” [33] when only two versions run.

For security. Kwon et al. [33] do dual execution for detecting information leaks and attacks. Salamat et al. [34] do multi-version execution also for sake of security, with the particularity of implementing the monitor entirely in userspace. In both cases, repair or patch generation is not considered. The idea of shadow traffic is closely related to the idea of shadow executions introduced by Capizzi et al. [35]. However, the goals are completely different. In their case, they aim at isolating all private information from a program interacting on the network, our goal is to perform patch search and regression testing.

For performance. Trachsel and Gross [32] perform parallel execution in order to speed up programs. The instances that are run in parallel are different implementations of the same algorithm or different binary versions compiled with different optimization options. The result of the fastest versions is the one kept for proceeding the computation. Compared to BikiniRepair, there is no actionable feedback given to the developer.

For reliability. Hosek and Cadar [31] do multi-version execution over versions and switch between versions when a bug is detected. This technique can handle failures because some bugs disappear while others appear between versions. This is not really compatible with the ideas presented in this paper, one hardly imagines mixing two different versions a huge source code patch with switch cases.

For regression testing. The big software companies use shadow traffic to perform regression testing when they put a new version online. For instance, Twitter maintains the open-source tool Diffy and Gor is also popular for this. Neither Diffy nor Gor perform regression testing on automatically synthesized patches.

VI. Conclusion

In this paper, we have presented the BikiniRepair approach for generating patches in production, requiring neither a failing test case nor a regression test suite. The failure detection that triggers the patch search is achieved with runtime assertions, and the regression assessment is done on live production traffic. BikiniRepair uses shadow traffic so that patch search and regression assessment is done in a fully sandboxed environment, with no interference with the production data. We have implemented the BikiniRepair approach for repairing null pointer dereferences in Java code and evaluated it on two real bugs from an open-source e-commerce application, for which respectively 104 and 5 patches are synthesized in the production environment. Our future work now consists of devising an approach to systematically and automatically store a shadow of the production state, and efficiently synchronize the shadow state with the actual production state.

15Diffy is available on github: https://github.com/twitter/Diffy
16Gor is available on github: https://github.com/buger/gor
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