BuildSheriff: Change-Aware Test Failure Triage for Continuous Integration Builds

Chen Zhang*
School of Computer Science
Fudan University
Shanghai, China

Bihuan Chen*†
School of Computer Science
Fudan University
Shanghai, China

Xin Peng*
School of Computer Science
Fudan University
Shanghai, China

Wenyun Zhao*
School of Computer Science
Fudan University
Shanghai, China

ABSTRACT

Test failures are one of the most common reasons for broken builds in continuous integration. It is expensive to diagnose all test failures in a build. As test failures are usually caused by a few underlying faults, triaging test failures with respect to their underlying root causes can save test failure diagnosis cost. Existing failure triage methods are mostly developed for triaging crash or bug reports, and hence not applicable in the context of test failure triage in continuous integration. In this paper, we first present a large-scale empirical study on 163,371 broken builds caused by test failures to characterize test failures in real-world Java projects. Then, motivated by our study, we propose a new *change-aware* approach, BuildSheriff, to triage test failures in each continuous integration build such that test failures with the same root cause are put in the same cluster. Our evaluation on 200 broken builds has demonstrated that BuildSheriff can significantly improve the state-of-the-art methods on the triaging effectiveness.

CCS CONCEPTS

• **Software and its engineering → Software testing and debugging**.

KEYWORDS

Test Failures, Failure Triage, Continuous Integration

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*Also with Shanghai Key Laboratory of Data Science, and Shanghai Collaborative Innovation Center of Intelligent Visual Computing.
†Bihuan Chen is the corresponding author.

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1 INTRODUCTION

Continuous integration (CI) [20] has gained widespread use and continued growth [21, 50] as it helps detect integration errors earlier, enhance developer productivity, and reduce development risk [31, 66]. Each integration is verified by an automated build that includes dependency installation, code compilation, static analysis, and test case execution. However, CI builds often break (i.e., fail), and developers need to spend much effort in troubleshooting broken builds [30]. As evidenced by several recent studies with open-source and industrial projects [8, 34, 37, 55, 67], test failures are one of the most frequent types of CI build failures; e.g., test failures are responsible for 59.0% of broken builds in open-source Java projects [8]. Developers need to manually localize and repair the underlying faults of test failures in each build. However, it is non-trivial for developers to analyze test failures in a build because a build is not always triggered for every commit, and a build may change multiple source code files. In that sense, it is usually time-consuming and expensive to manually diagnose test failures in each build.

To reduce test failure diagnosis cost, a number of techniques have been proposed from different perspectives. One line of work tries to design fault localization techniques to automatically localize faults that cause test failures [27, 53, 70, 72, 74]. Another line of work tries to develop program repair techniques to automatically fix faults [48]. Orthogonal to these two types of techniques, test failure triage techniques are designed to cluster test failures that are caused by the same fault into the same cluster [25, 26]. In this way, test failure diagnosis can be realized by only analyzing one test failure in each cluster but not all the test failures, which can reduce manual diagnosis cost or boost automated fault localization and program repair techniques.

Existing failure triage methods are mostly designed to triage crash or bug reports. Sharing the same problem as test failures in CI builds, multiple reports can be filed for the same fault. These methods can be grouped into stack trace-based (e.g., [10, 15, 17, 43]), profiling-based (e.g., [14, 22, 44, 52]), and text-based methods (e.g., [3, 57, 61, 62]), depending on what information (i.e., stack traces, execution profiles, and textual descriptions) is used to measure failure similarity.

Unfortunately, stack trace-based methods are not applicable in the context of test failure triage in CI because *they are not designed for test failures in CI, and are not aware of the test failure characteristics and potentially valuable knowledge in CI for better triage.* First, we show in our study (Sec. 2.1) that 73.2% of broken builds with test failures are caused

by assertion failures, which do not report any informative exception stack trace. As a result, stack trace-based methods could have a poor performance on triaging assertion failures. Second, we also report in our study (Sec. 2.1) that test failures in 78.5% of the 200 randomly selected broken builds share one root cause. Hence, stack trace-based methods could tend to triage test failures into one single cluster such that they could still yield an overall good performance although they have a poor performance on triaging test failures into multiple clusters. Third, code changes in CI builds, a valuable knowledge in CI but not available in crash or bug reports, usually have a great impact on test results [46]. Thus, stack trace-based methods, simply relying on stack traces without taking into account code changes, could be less effective. Profiling-based and text-based methods are also not applicable to test failure triage in CI because execution profiles would impose too large overhead to be practically used in CI [46] while textual descriptions (which are often written by users in crash or bug reports) of test failures are not produced during automated CI builds.

In this paper, we first present a large-scale empirical study, using 163,371 broken builds caused by test failures from 1,337 GitHub Java projects, to understand test failures in CI builds. We characterize the prevalence of two types of test failures (i.e., exception failures and assertion failures), and motivate the potential value and the design insights of test failure triage. Then, we propose a new *change-aware* approach, BuildSheriff, to triage test failures for CI builds so that test failures with the same root cause are put to the same cluster. The key idea of BuildSheriff is to consider code changes as important triage knowledge as root causes of test failures are often introduced by code changes [75]. We develop a pipeline of three strategies based on complexity of code changes, change-aware stack trace similarity, and exception message similarity for exception failure triage, and a pipeline of two strategies based on complexity of code changes and change-aware test code similarity for assertion failure triage. To the best of our knowledge, this is the first work to triage test failures in general CI.

To evaluate the effectiveness and efficiency of BuildSheriff, we compared it with one naive method and three state-of-the-art methods [12, 15, 17] on 200 broken builds with respect to 20 metrics. Our evaluation results have demonstrated that i) BuildSheriff can significantly improve the naive method on 13 of the 20 metrics (e.g., by 14%+ on the number of correctly triaged builds, and 77%+ on the number of missed root causes); ii) BuildSheriff can significantly improve the best of the state-of-the-art methods on 15 of the 20 metrics (e.g., by 45%+ on the number of correctly triaged builds, and 28%+ on test failure inspection effort saving) and slightly improve the best of the state-of-the art methods on 4 of the 20 metrics; and iii) the average time overhead to triage a build is 1.61 seconds.

In summary, this paper makes the following contributions.

- We conducted a large-scale empirical study to characterize test failures in real-world Java projects and motivate test failure triage.
- We proposed a new change-aware approach, BuildSheriff, to triage test failures in CI builds effectively and practically.
- We conducted experiments on 200 broken builds to demonstrate the effectiveness and efficiency of BuildSheriff.

2 MOTIVATION

In this section, we first present an empirical study of test failures, and then introduce motivating examples of test failures.

2.1 An Empirical Study of Test Failures

Data Set. To construct the data set for our empirical study of test failures, we start with the data set proposed by Zhang et al. [73], which includes the CI build history of 3,799 Java projects on GitHub. To the best of our knowledge, it is the largest available data set of CI builds. To ease the extraction of test failure information from build logs, we focus on projects that use Maven as the automated build tool, which results in 1,763 projects. To further ensure that CI is commonly used, we exclude the projects that only have less than 100 builds, which restricts our selection to 1,739 projects with a total of 3,981,842 builds. Of these builds, 833,209 (20.9%) builds have a build state of *errored* or *failed*, which are also known as *broken* builds. In particular, 163,371 (19.6%) of these broken builds, covering 1,337 projects, are caused by test failures, which is lower than the 59.0% as reported by Beller et al. [8] (using 423 Java projects). The difference may be due to the different scale of studies. Still, test failure is a non-negligible failure type of broken builds, and affects many of the Java projects. Notice that a test is considered as failed in CI if it throws an exception (i.e., *exception failure*) or fails an assertion (i.e., *assertion failure*), and the build log from Maven projects also provides a summary of the number of tests that signals exception failures and assertion failures.

Research Questions. Using 163,371 broken builds with test failures (hereafter referred to as test-failed builds) from 1,337 projects, our study is designed to answer the following research questions.

RQ1: How many test-failed builds in a project exhibit the symptom of exception and assertion failures during test execution?
RQ2: How many tests in a test-failed build signal exception and assertion failures during test execution?
RQ3: How many root causes affect failed tests in a test-failed build?

In **RQ1**, we measure for each project the ratio of test-failed builds that exhibit the symptom of exception and assertion failures during test execution, and compute the ratio distribution across all projects. Our results from **RQ1** aim to characterize the prevalence of both exception and assertion failures, and motivate the need for a triage approach to support both of them. In **RQ2**, we measure for each test-failed build the number of all tests and the number of tests that signal exception and assertion failures, and compute their distribution across all test-failed builds. In **RQ3**, we randomly select 100 test-failed builds with exception failures and 100 test-failed builds with assertion failures, manually triage the failed tests via locating their root causes, and report the distribution of the number of root causes. Our results from **RQ2** and **RQ3** aim to motivate the potential value of triaging test failures in CI, and demonstrate the specific characteristics of test failures in CI to better design a triage approach.

Test-Failed Build Analysis (RQ1). Overall, 80,778 (49.4%) of the 163,371 test-failed builds, covering 1,154 projects, exhibit the symptom of exception failures, and 119,514 (73.2%), covering 1,246 projects, exhibit the symptom of assertion failures. In detail, Fig. 1a shows the distribution of the ratio of test-failed builds that have exception failures and assertion failures across all projects in violin plot. The three lines in each plot respectively denote the upper quartile, the median and the lower quartile. We can see that at least 24.1%, 58.8% and 85.7% of the test-failed builds contain exception failures in 75%, 50% and 25% of the projects, whereas more than 55.8%, 81.1% and 100% of the test-failed builds have assertion failures in 75%, 50% and 25% of the projects. These results indicate that assertion failures are even more common

(a) The Ratio of Test-Failed Builds **(b) The Number of Failed Tests** **(c) The Number of Root Causes**

Figure 1: Distributions of the Ratio of Test-Failed Builds, the Number of Failed Tests, and the Number of Root Causes

than exception failures to cause test-failed builds. Therefore, test failure triage in CI should support both exception and assertion failures, and existing stack trace-based failure triage techniques, which mainly support exception failures, are not directly applicable in CI.

Failed Test Analysis (RQ2). Fig 1b reports the distribution of the number of all tests (in the left violin plot) and the number of failed tests (in the right violin plot) across the 80,778 test-failed builds that have exception failures and the 119,514 test-failed builds that have assertion failures in logarithmic scale. We can observe that in 75%, 50% and 25% of the test-failed builds that have exception failures, there are at least 50, 403 and 1,636 tests, while at least 1, 3 and 9 tests signal exception failures; and in 75%, 50% and 25% of the test-failed builds that have assertion failures, there are at least 132, 536 and 2,000 tests, while at least 1, 2 and 4 tests signal assertion failures. Compared to the number of all tests, the number of failed tests is relatively very small. In particular, 52,586 of the 80,778 test-failed builds have at least two tests signal exception failures, and their median number of tests signaling exception failures is 6, while 62,494 of the 119,514 test-failed builds have at least two tests signal assertion failures, and their median number of tests signaling assertion failures is 4. These results demonstrate that multiple test failures are moderately common in CI builds, which represents the potential reduction of test failure diagnosis cost that can be achieved by test failure triage.

Root Cause Analysis (RQ3). We randomly pick 100 test-failed builds that have at least two tests signal exception failures and 100 test-failed builds that have at least two tests signal assertion failures, achieving a confidence level of 95% and a margin of error of 9.8%. It is worth mentioning that over 30% of these 200 broken builds were triggered after more than two commits, and on average, around nine source code files were changed in each of the 200 broken build. Thus, it is non-trivial for developers to diagnose test failures in a build. Two of the authors separately diagnose failed tests in these 200 test-failed builds by investigating the previous commits that may introduce the failure, the succeeding commits that may fix the failure and the build log in order to identify the root cause for each failed test. We define a root cause as the code changes that introduce the failure. Then, they investigate inconsistent cases together to reach consensus. We spent around 1.5 person-month to complete the manual analysis. Fig. 1c reports the manual triage results, i.e., the distribution of the number of root causes across the 200 test-failed builds. We can see that the failed tests with exception failures have the same root cause in 82 builds, and have multiple root causes in 18 builds. The failed tests with assertion failures have the same root cause in 75 builds, and have multiple root causes in 25 builds. These results indicate that test failures in a large part of the test-failed builds have only one root cause. Thus, test failure triage in CI should be aware of this specific characteristic. Existing stack trace-based failure triage techniques fail to do so, and their triage model tends to triage test failures into one root cause such that it can still yield an overall good performance although it has a poor performance on triaging test failures with multiple root causes.

```
testNumDecompositionLevelsLossless(loci.formats.utests.JAIIIOServiceTest)  Time elapsed: 0.259 sec  <<< FAILURE!
java.io.IOException: closed
mDt_e  at javax.imageio.stream.ImageInputStreamImpl.checkClosed(ImageInputStreamImpl.java:110)
mDt_e  at javax.imageio.stream.ImageInputStreamImpl.close(ImageInputStreamImpl.java:857)
mDt_e  at javax.imageio.stream.MemoryCacheImageInputStream.close(MemoryCacheImageInputStream.java:173)
0      at loci.formats.services.JAIIIOServiceImpl.readImage(JAIIIOServiceImpl.java:153)
3      at loci.formats.utests.JAIIIOServiceTest.testNumDecompositionLevelsLossless(JAIIIOServiceTest.java:272)
```

(a) Exception Failure in Test `testNumDecompositionLevelsLossless`

```
testReadRasterLevel0Lossy(loci.formats.utests.JAIIIOServiceTest)  Time elapsed: 0.022 sec  <<< FAILURE!
java.io.IOException: closed
mDt_e  at javax.imageio.stream.ImageInputStreamImpl.checkClosed(ImageInputStreamImpl.java:110)
mDt_e  at javax.imageio.stream.ImageInputStreamImpl.close(ImageInputStreamImpl.java:857)
mDt_e  at javax.imageio.stream.MemoryCacheImageInputStream.close(MemoryCacheImageInputStream.java:173)
0      at loci.formats.services.JAIIIOServiceImpl.readRaster(JAIIIOServiceImpl.java:179)
3      at loci.formats.utests.JAIIIOServiceTest.testReadRasterLevel0Lossy(JAIIIOServiceTest.java:223)
```

(b) Exception Failure in Test `testReadRasterLevel0Lossy`

```
testSaveBytesTiling(loci.formats.utests.out.TiffWriterTest)  Time elapsed: 0.185 sec  <<< FAILURE!
loci.formats.FormatException: Could not decompress JPEG2000 image...
mDt_e  at javax.imageio.stream.ImageInputStreamImpl.checkClosed(ImageInputStreamImpl.java:110)
mDt_e  at javax.imageio.stream.ImageInputStreamImpl.close(ImageInputStreamImpl.java:857)
mDt_e  at javax.imageio.stream.MemoryCacheImageInputStream.close(MemoryCacheImageInputStream.java:173)
0      at loci.formats.services.JAIIIOServiceImpl.readRaster(JAIIIOServiceImpl.java:179)
1      at loci.formats.codec.JPEG2000Codec.decompress(JPEG2000Codec.java:296)
2      at loci.formats.tiff.TiffCompression.decompress(TiffCompression.java:279)
1      at loci.formats.tiff.TiffParser.getTile(TiffParser.java:739)
1      at loci.formats.tiff.TiffParser.getSamples(TiffParser.java:982)
1      at loci.formats.tiff.TiffParser.getSamples(TiffParser.java:779)
2      at loci.formats.in.MinimalTiffReader.openBytes(MinimalTiffReader.java:296)
2      at loci.formats.FormatReader.openBytes(FormatReader.java:888)
2      at loci.formats.FormatReader.openBytes(FormatReader.java:859)
2      at loci.formats.utests.out.TiffWriterTest.checkImage(TiffWriterTest.java:585)
2      at loci.formats.utests.out.TiffWriterTest.testSaveBytesTiling(TiffWriterTest.java:523)
```

(c) Exception Failure in Test `testSaveBytesTiling`

Figure 2: Part of Exception Failures in `bioformats`

2.2 Motivating Examples of Test Failures

Fig. 2 shows the exception log of three of the 62 exception failures in a build of the project `bioformats`. The first line of the log includes the signature of the test that signals the exception failure. The second line shows the exception message that is composed of two parts, i.e., the exception type and a developer-written message. The rest of the lines list the exception stack trace. Fig. 3 shows the code changes that cause the exception failures. The call to `mciis.close()` was inserted after `reader.dispose()` in method `readImage` in Fig. 3a, causing the failure in Fig. 2a. Similarly, the call to `mciis.close()` was inserted after `reader.dispose()` in method `readRaster` in Fig. 3b, which caused the failures in Fig. 2b and 2c. In fact, the code change in Fig. 3a caused six of the 62 exception failures, and the code change in

```
public BufferedImage readImage(InputStream in,
JPEG2000CodecOptions options) throws IOException, ServiceException {
        ......
        BufferedImage image = reader.read(0, param);
        reader.dispose();
+       mciis.close();
        return image;
}
```

(a) Code Changes in `readImage` in `JAIIIOServiceImpl.java`

```
public Raster readRaster(InputStream in, JPEG2000CodecOptions
options) throws IOException, ServiceException {
        ......
        Raster raster = reader.readRaster(0, param);
        reader.dispose();
+       mciis.close();
        return raster;
}
```

(b) Code Changes in `readRaster` in `JAIIIOServiceImpl.java`

Figure 3: Part of Code Changes in `bioformats`

Fig. 3b caused the remaining 56 exception failures. To fix the failures, `mciis.close()` should be called before `reader.dispose()`. Our approach can successfully triage the 62 exception failures into two clusters with respect to the two root causes (details will be introduced in Sec. 3.3). It is also worth mentioning that the two root causes share the same nature but occur in different code locations, and hence we consider them as two root causes but not one root cause.

Fig. 4 presents the exception log of the two assertion failures in a build of the project `retrofit`. The first line of the log includes the signature of the test that signals the assertion failure. The next five lines report the assertion message that is composed of two parts, i.e., the assertion error type and the expected and actual value in the assertion statement. The remaining lines show the exception stack trace. Fig. 5 shows the test code of the two failed tests, and Fig. 6 shows the code changes that cause the assertion failures. The code changes in Fig. 6a renamed `converterFactory` to `factory`, while the code changes in Fig. 6b renamed `callbackExecutor` to `executor`. The two renaming refactorings were not consistently applied on the assertion statements in the two tests in Fig. 5, which caused the failures in Fig. 4. To fix the failures, the same renaming refactorings should be applied on the two tests. Our approach can correctly triage the two assertion failures into two clusters with respect to the two root causes, i.e., the two renaming refactorings (details will be introduced in Sec. 3.4).

3 APPROACH

In this section, we first present an overview of BuildSheriff, and then introduce each step of BuildSheriff in detail.

3.1 Overview

Fig. 7 presents the overview of our change-aware test failure triage approach. BuildSheriff is designed to triage failed tests in each CI build of a target project so that the failed tests with the same root cause are put in the same cluster. BuildSheriff is triggered when a CI build from a project repository occurs. It works in three steps: *triage knowledge preparation* (Sec. 3.2), *exception failure triage* (Sec. 3.3), and *assertion failure triage* (Sec. 3.4). It first prepares triage knowledge by analyzing the build log, the project source code, and the code changes from the previous passed build. Based on the triage knowledge, it then uses different strategies to triage exception failures and assertion failures. The key characteristic of our triage strategies is the awareness

```
callbackExecutorNullThrows(retrofit2.RetrofitTest)  Time elapsed: 0.029 sec  <<< FAILURE!
java.lang.AssertionError:
Expecting message:
 <"callbackExecutor == null">
but was:
 <"executor == null">
    at retrofit2.RetrofitTest.callbackExecutorNullThrows(RetrofitTest.java:1057)
    at sun.reflect.NativeMethodAccessorImpl.invoke0(Native Method)
    ......
    at org.junit.runners.model.FrameworkMethod$1.runReflectiveCall(FrameworkMethod.java:50)
    ......
    at org.apache.maven.surefire.booter.ForkedBooter.main(ForkedBooter.java:75)
```

(a) Assertion Failure in Test `callbackExecutorNullThrows`

```
converterNullThrows(retrofit2.RetrofitTest)  Time elapsed: 0.002 sec  <<< FAILURE!
java.lang.AssertionError:
Expecting message:
 <"converterFactory == null">
but was:
 <"factory == null">
    at retrofit2.RetrofitTest.converterNullThrows(RetrofitTest.java:744)
    at sun.reflect.NativeMethodAccessorImpl.invoke0(Native Method)
    ......
    at org.junit.runners.model.FrameworkMethod$1.runReflectiveCall(FrameworkMethod.java:50)
    ......
    at org.apache.maven.surefire.booter.ForkedBooter.main(ForkedBooter.java:75)
```

(b) Assertion Failure in Test `converterNullThrows`

Figure 4: Assertion Failures in `retrofit`

```
@Test public void callbackExecutorNullThrows() {
        try {
                new Retrofit.Builder().callbackExecutor(null);
                fail();
        } catch (NullPointerException e) {
                assertThat(e).hasMessage("callbackExecutor == null");
        }
}
```

(a) Code of Test `callbackExecutorNullThrows`

```
@Test public void converterNullThrows() {
        try {
                new Retrofit.Builder().addConverterFactory(null);
                fail();
        } catch (NullPointerException e) {
                assertThat(e).hasMessage("converterFactory == null");
        }
}
```

(b) Code of Test `converterNullThrows`

Figure 5: Test Code in `retrofit`

```
-   public Builder addConverterFactory(Converter.Factory converterFactory) {
-   converterFactories.add(checkNotNull(converterFactory, "converterFactory == null"));
+   public Builder addConverterFactory(Converter.Factory factory) {
+       converterFactories.add(checkNotNull(factory, "factory == null"));
        return this;
    }
```

(a) Code Changes in `addConverterFactory`

```
-   public Builder callbackExecutor(Executor callbackExecutor) {
-   this.callbackExecutor = checkNotNull(callbackExecutor, "callbackExecutor == null");
+   public Builder callbackExecutor(Executor executor) {
+       this.callbackExecutor = checkNotNull(executor, "executor == null");
        return this;
    }
```

(b) Code Changes in `callbackExecutor`

Figure 6: Part of Code Changes in `retrofit`

of code changes. BuildSheriff is currently implemented for Java projects that use Travis as CI service and Maven as build tool.

3.2 Triage Knowledge Preparation

BuildSheriff has three steps to prepare the triage knowledge for exception failures and assertion failures. The triage knowledge is threefold: *test failures* (i.e., test signature, exception message, stack trace, and test code), *code changes* at the file, method and field level that potentially cause the test failures, and *file dependencies* that capture the code change impacts that also potentially cause the test failures.

Test Failure Analysis. As the build log contains a well-formatted summary of test failures, we first use regular expression matching to

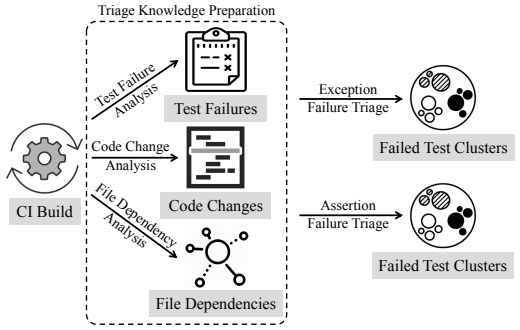


Figure 7: Approach Overview of BuildSheriff

extract two sets of failed tests that respectively signal exception failures and assertion failures, and parse the test signature *sig* (i.e., class name and test method name) and the line number of the test code that signals the failure for each of the failed tests. If no test failure occurs (i.e., the build is not a test-failed build), BuildSheriff stops.

Then, for a failed test signaling an exception failure, we use its test signature to locate and parse the exception message *msg* and the stack trace *st* from the build log. The exception message contains the exception type and a developer-written message, while the stack trace consists of an ordered list of frames (i.e., methods) that were active on the call stack before the exception occurred. Generally, if two exception failures share the same root cause, they are more likely to be similar in the exception message and the stack trace. Differently, for a failed test that signals an assertion failure, we do not extract the assertion message and the stack trace because of their low discrimination. Specifically, the assertion messages in the build log mostly contain the same error type (e.g., `java.lang.AssertionError`), while the stack traces mostly consist of similar methods that do not belong to the target project but are assertion-related methods from the testing infrastructure (e.g., JUnit) as the methods before the assertion statement in the tests successfully returned. In that sense, assertion failures that have different root causes could have similar assertion messages and stack traces. For example, all the frames except for the first frame in the two stack traces in Fig. 4 are methods from Java reflection, JUnit and Maven, and are exactly the same, although the two assertion failures have different root causes.

Finally, for a failed test that signals an assertion failure, we obtain the test method from the project source code according to its test signature, and tailor the test code *tc* from the first line of the test method to the line number of the test code that signals the assertion failure. In other words, only the executed test code is included in *tc* because the unexecuted test code is actually not related to the test failure. However, for a failed test signaling an exception failure, we do not tailor the test code as the triage knowledge. The reason is that tests signaling exception failures, compared to tests signaling assertion failures, are mostly partially executed, and hence the executed test code contains less informative knowledge for exception failure triage.

Formally, we define an exception failure x_e in the exception failures $\mathcal{X}_e$ of a build as a 3-tuple $\langle sig, msg, st \rangle$, and define an assertion failure x_a in the assertion failures $\mathcal{X}_a$ of a build as a 2-tuple $\langle sig, tc \rangle$.

Code Change Analysis. Motivated by the fact that root causes of test failures are often introduced by code changes [75], we consider code changes as important triage knowledge. Instead of considering code changes from the previous build, we consider code changes from the previous passed build because all code changes in previous consecutive failed builds can potentially cause the test failures in the current build. To this end, we use the code differencing tool ClDiff [33] to obtain the changed source code files $\mathcal{F}_c$, methods $\mathcal{M}_c$ and fields $\mathcal{D}_c$ from the previous passed build to the current build.

File Dependency Analysis. Code affected by the code changes can also potentially cause test failures. Thus, we use code dependencies to capture such code change impacts and sever as the triage knowledge. We model code dependencies at the file-level rather than method-level granularity for two reasons. On one hand, we are inspired by recent studies on practical regression test selection [24, 42], which show that better results can be achieved by selecting tests at a coarser (file-level) compared to a finer (method-level) granularity of code dependencies. On the other hand, it is more efficient to analyze file dependencies than method dependencies, which is important for practical failure triage in CI. Specifically, we adopt an incremental way to analyze file dependencies. We first construct a file dependency graph $\mathcal{G} = \langle \mathcal{V}, \mathcal{E} \rangle$ for the target project when the first test-failed build occurs. Each node in $\mathcal{V}$ denotes a source code file, and each edge in $\mathcal{E}$ denotes a usage dependency between two files. A file can use all files from its own package, or files from other packages via import statement or fully qualified name. Thus, we use JDT to parse each source code file, i.e., to parse its own package and import statements to identify potentially used files and establish usage dependencies. Here we do not analyze file usages with fully qualified name due to its heavy-weight analysis cost and its uncommon adoption. Note that this step is a one-time job for the target project. Then, we update $\mathcal{G}$ for each subsequent test-failed build by parsing changed (i.e., deleted, added, and modified) files from the previous test-failed build.

3.3 Exception Failure Triage

BuildSheriff achieves the triage of exception failures $\mathcal{X}_e$ in a build by a pipeline of the following three strategies.

$\mathbf{S}_e^1$: Complexity of Code Changes. Generally, the higher complexity of code changes in a build, the higher chance of causing test failures, and the larger number of root causes for test failures. However, CI requires developers to frequently merge their code to find errors as early as possible. Therefore, code changes in a build are mostly not complex, and as revealed by our study (Sec. 2.1), a large part of test-failed builds have only one root cause for test failures. Motivated by these observations, we propose a strategy $\mathbf{S}_e^1$ to use the complexity of code changes to determine whether $\mathcal{X}_e$ has one root cause or not. Here, we use the number of changed methods (i.e., $|\mathcal{M}_c|$) as the indicator of code change complexity, and consider $\mathcal{X}_e$ as having one root cause if $|\mathcal{M}_c|$ is lower than a threshold Δ_e (i.e., $|\mathcal{M}_c| \leq \Delta_e$). Thus, if $|\mathcal{M}_c| \leq \Delta_e$ is satisfied, BuildSheriff triages all exception failures into one cluster; otherwise, it uses the next strategy in the pipeline.

$\mathbf{S}_e^2$: Change-Aware Stack Trace Similarity. A stack trace is an ordered list of frames on the call stack when an exception occurred. Each frame represents a method, and records its enclosing file name. A stack trace carries important information for debugging [59]. We propose a new change-aware stack trace similarity metric based on the insight that a higher weight should be given to the frames that are closer to code changes because such frames are more likely to be affected by code changes and be blamed for the exception. Based on this metric, we propose a clustering strategy $\mathbf{S}_e^2$ to triage $\mathcal{X}_e$.

Based on the above insight, we first define the distance of a frame m to code changes, as formulated in Eq. 1, where f_m denotes the enclosing file of m, and $dt'(f_m, f_c, \mathcal{G})$ denotes the distance of f_m to a changed file $f_c \in \mathcal{F}_c$ on the file dependency graph $\mathcal{G}$. Basically, $dt(m)$ is zero if m itself is changed, and one if the enclosing file of m is changed; otherwise, $dt(m)$ is measured by the minimum distance of f_m to all changed files on $\mathcal{G}$ if f_m reaches some changed file, and a large value mDt_e if f_m does not reach any changed file.

$$dt(m) = \begin{cases} 0, & m \in \mathcal{M}_c \\ 1, & f_m \in \mathcal{F}_c \\ 1 + min_{f_c \in \mathcal{F}_c} dt'(f_m, f_c, \mathcal{G}) & f_m \ reach \ some \ f_c \\ mDt_e & otherwise \end{cases} \quad (1)$$

Then, we define the weight (or importance) of a frame m based on the distance to code changes $dt(m)$, as formulated in Eq. 2, where c_e is a coefficient for the distance to code changes. The smaller the distance to code changes, the higher the weight.

$$w(m) = e^{-c_e * dt(m)} \quad (2)$$

Then, we define the similarity of two stack traces $st_1 = \{m_1^1, m_2^1, ...\}$ and $st_2 = \{m_1^2, m_2^2, ...\}$ using the Sørensen-Dice index [18] (i.e., Eq. 3).

$$sim(st_1, st_2) = \frac{2 * \sum_{m \in st_1 \cap st_2} w(m)}{\sum_{m \in st_1} w(m) + \sum_{m \in st_2} w(m)} \quad (3)$$

Finally, we apply the single-linkage agglomerative clustering technique [16] to cluster exception failures $\mathcal{X}_e$ based on the similarity of the stack traces of exception failures. In other words, we use the maximum stack trace similarity of all exception failure pairs between two clusters as the cluster distance, as formulated in Eq. 4, where $\mathcal{X}_e^1$ and $\mathcal{X}_e^2$ are two clusters of exception failures; and we use a cluster distance threshold dt_{st} as a stopping criterion for clustering.

$$dt(\mathcal{X}_e^1, \mathcal{X}_e^2) = max_{x_e^1 \in \mathcal{X}_e^1, x_e^2 \in \mathcal{X}_e^2} sim(x_e^1.st, x_e^2.st) \quad (4)$$

When the stack trace size (i.e., the number of frames) of an exception failure is small, the stack trace contains less informative knowledge for failure triage. Hence, we use $\mathbf{S}_e^2$ if the maximum stack trace size of the exception failures is larger than a size threshold $size_{st}$ (i.e., $max_{x_e \in \mathcal{X}_e} |x_e.st| \geq size_{st}$); otherwise, we use the next strategy.

$\mathbf{S}_e^3$: Exception Message Similarity. An exception message contains the exception type and a developer-written message, which potentially describes the root cause, symptom, or handling hint of the exception. Intuitively, two exception failures having the same root cause are likely to have similar exception messages. Hence, we design a clustering strategy $\mathbf{S}_e^3$ based on exception message similarity to triage $\mathcal{X}_e$.

First, we define the similarity of two exception messages msg_1 and msg_2 based on their Levenshtein distance at the token level, as formulated in Eq. 5, where $t(msg)$ denotes a sequence of tokens in msg split by white space, and $dt(t(msg_1), t(msg_2))$ denotes the Levenshtein distance, i.e., the minimum number of token-level edits (i.e., insertion, deletion and substitution) to change $t(msg_1)$ into $t(msg_2)$.

$$sim(msg_1, msg_2) = \frac{maxLength - dt(t(msg_1), t(msg_2))}{maxLength}$$
$$maxLength = max(|t(msg_1)|, |t(msg_2)|) \quad (5)$$

We then apply the single-linkage agglomerative clustering technique to cluster exception failures $\mathcal{X}_e$ based on the similarity of the exception messages of exception failures (i.e., Eq. 6). We use a cluster distance threshold dt_{msg} as a stopping criterion for clustering.

$$dt(\mathcal{X}_e^1, \mathcal{X}_e^2) = max_{x_e^1 \in \mathcal{X}_e^1, x_e^2 \in \mathcal{X}_e^2} sim(x_e^1.msg, x_e^2.msg) \quad (6)$$

Example. Given exception failures in Fig. 2, BuildSheriff adopts $\mathbf{S}_e^2$ to achieve the triage. The distance of each frame to code changes is highlighted in the left of each frame in Fig. 2. As explained in Sec. 2.2, the exception failures in Fig. 2a and 2b had different root causes, even though their stack traces look similar. On the other way around, the exception failures in Fig. 2b and 2c had the same root cause, even though their stack traces look dissimilar. BuildSheriff correctly triages them due to our consideration of the distance of each frame to code changes in computing stack trace similarity. In detail, BuildSheriff gives the highest weight to the frame of `readImage` and `readRaster` because they are changed (as shown in Fig. 3). With such weighted similarity measure, BuildSheriff successfully triages the failures in Fig. 2a and 2b into two clusters, as the stack trace in Fig. 2a contains `readImage` but not `readRaster` and the stack trace in Fig. 2b contains `readRaster` but not `readImage`; and it also correctly triages the failures in Fig. 2b and 2c into the same cluster, as both stack traces in Fig. 2b and 2c contain `readRaster`. The state-of-the-art method [15] fails on these cases.

3.4 Assertion Failure Triage

BuildSheriff achieves the triage of assertion failures $\mathcal{X}_a$ in a build by a pipeline of the following two strategies.

$\mathbf{S}_a^1$: Complexity of Code Changes. Similar to exception failure triage, we propose a strategy $\mathbf{S}_a^1$ to use the complexity of code changes to determine whether $\mathcal{X}_a$ has one root cause or not. We regard $\mathcal{X}_a$ as having one root cause if the number of changed methods (i.e., $|\mathcal{M}_c|$) is lower than a threshold Δ_a (i.e., $|\mathcal{M}_c| \leq \Delta_a$). Thus, if $|\mathcal{M}_c| \leq \Delta_a$ is satisfied, BuildSheriff triages all the failed tests into one cluster; otherwise, it uses the next strategy in the pipeline.

$\mathbf{S}_a^2$: Change-Aware Test Code Similarity. The test code tc of an assertion failure is the executed code when the assertion failure occurred. Intuitively, a higher test code similarity between two assertion failures, a higher likelihood that they share the same root cause. Similar to our change-aware stack trace similarity metric, we design a change-aware test code similarity metric based on the insight that a higher weight should be assigned to code tokens that are closer to code changes as such code tokens are more likely to be affected by code changes and be blamed for the assertion failure. Using this metric, we develop a clustering strategy $\mathbf{S}_a^2$ to triage $\mathcal{X}_a$.

Based on the above insight, we first tokenize test code tc into a list of code tokens $\{t_1, t_2, ...\}$. Then, we define the distance of a code token t to code changes, as formulated in Eq. 7, where f_t denotes the enclosing file of t if t corresponds to the name of a method or a field, and $dt'(f_t, f_c, \mathcal{G})$ denotes the distance of f_t to a changed file $f_c \in \mathcal{F}_c$ on the file dependency graph $\mathcal{G}$. Basically, $dt(t)$ is zero if t is changed and corresponds to the name of a method or a field, and one if f_t is changed; otherwise, $dt(t)$ is measured by the minimum distance of f_t to all changed files on $\mathcal{G}$ if f_t reaches some changed file, and a large value mDt_a if f_t does not reach any changed file.

$$dt(t) = \begin{cases} 0, & t \in \mathcal{M}_c \cup \mathcal{D}_c \\ 1, & f_t \in \mathcal{F}_c \\ 1 + min_{f_c \in \mathcal{F}_c} dt'(f_t, f_c, \mathcal{G}) & f_t \ reach \ some \ f_c \\ mDt_a & otherwise \end{cases} \quad (7)$$

Then, we define the weight (or importance) of a code token t based on the distance to code changes $dt(t)$, as formulated in Eq. 8, where c_a is a coefficient for the distance to code changes.

$$w(t) = e^{-c_a * dt(t)} \tag{8}$$

Then, we define the similarity of two test code $tc_1 = \{t_1^1, t_2^1, ...\}$ and $tc_2 = \{t_1^2, t_2^2, ...\}$ using the Sørensen-Dice index [18] (i.e., Eq. 9).

$$sim(tc_1, tc_2) = \frac{2 * \sum_{t \in tc_1 \cap tc_2} w(t)}{\sum_{t \in tc_1} w(t) + \sum_{t \in tc_2} w(t)} \tag{9}$$

We finally use the single-linkage agglomerative clustering technique to cluster assertion failures $\mathcal{X}_a$ based on the similarity of the test code of exception failures (i.e., Eq. 10). We use a cluster distance threshold dt_{tc} as a stopping criterion for clustering.

$$dt(\mathcal{X}_a^1, \mathcal{X}_a^2) = max_{x_a^1 \in \mathcal{X}_a^1, x_a^2 \in \mathcal{X}_a^2} sim(x_a^1.tc, x_a^2.tc) \tag{10}$$

Example. Given assertion failures in Fig. 4, BuildSheriff adopts $\mathbf{S}_a^2$ to realize the triage. The code tokens of the test in Fig. 5a are "try", "new", "Retrofit", "Builder", "callbackExecutor", "null", "fail", "catch", "NullPointerException", "e", "assertThat", "e", "hasMessage" and "callbackExecutor == null". "Retrofit", "Builder" and "callbackExecutor" respectively have a distance of 1, 1 and 0 to code changes, and other code tokens have a distance of mDt_a to code changes. Similarly, "Retrofit", "Builder" and "addConverterFactory" in Fig. 5b respectively have a distance of 1, 1 and 0 to code changes. As introduced in Sec. 2.2, the assertion failures in Fig. 4 had different root causes, even though their failed tests in Fig. 5 look similar. BuildSheriff successfully triages them because of our consideration of the distance of each test code token to code changes in computing test code similarity. Specifically, BuildSheriff gives the highest weight to "callbackExecutor" and "addConverterFactory" because the corresponding methods are changed (as shown in Fig. 6). As the test code token with the highest weight is different in the two tests, BuildSheriff correctly triages the two failures into two clusters with weighted similarity measure.

3.5 Usage Scenario of Triage Results

After triaging test failures, BuildSheriff presents developers with a set of clusters, and notifies developers that each cluster has a set of test failures whose root cause is considered as the same. For each test failure in a cluster, BuildSheriff provides developers with the distance information to code changes (e.g., Fig. 2), and tells developers that methods on stack traces or methods in test code that have small distance to code changes can be the starting point to locate root causes.

Then, developers can use the triage results in two potential scenarios. **Usage Scenario 1:** Developers are required to choose the first test failure in each cluster as the representative to find and fix root causes, and rerun all the tests. When some root causes are not fixed (i.e., some tests still fail), developers need to inspect all the remaining test failures in each cluster. **Usage Scenario 2:** Instead of inspecting all the remaining test failures in each cluster when some root causes are not fixed by inspecting the first test failure in each cluster, developers need to inspect the first test failure of the remaining test failures in each cluster, rerun all the tests, and iterate this process until all the root causes are fixed (i.e., all the tests pass).

The differences between the two usage scenarios are that more test failures are inspected by developers in **Usage Scenario 1** than in **Usage Scenario 2**, but more executions of all the tests are needed in **Usage Scenario 2** than in **Usage Scenario 1** (where at most two executions of all the tests are needed). In fact, the lower bound on the number of inspected test failures is achieved in **Usage Scenario 2** at the cost of more executions of all the tests. In other words, the two usage scenarios have a different tradeoff between the number of inspected test failures and the number of executions of all the tests. Practical usage scenarios can be in-between **Usage Scenario 1** and **Usage Scenario 2**. In that sense, the significance of BuildSheriff is that it reduces test failure diagnosis cost for CI developers by reducing the number of inspected test failures or the number of executions of all the tests through effectively triaging test failures.

4 EVALUATION

We have implemented BuildSheriff in 17.0K lines of Java code, and have released the code and data of BuildSheriff at our website [1].

4.1 Evaluation Setup

To evaluate the effectiveness and efficiency of BuildSheriff, we designed our evaluation to answer the following research questions.

- **RQ4**: How is the effectiveness of BuildSheriff in triaging test failures, compared with the state-of-the-art approaches? (Sec. 4.2)
- **RQ5**: How is the efficiency of BuildSheriff in triaging test failures, compared with the state-of-the-art approaches? (Sec. 4.3)
- **RQ6**: How is the contribution of each triage strategy in BuildSheriff to the achieved effectiveness of BuildSheriff? (Sec. 4.4)
- **RQ7**: How is the sensitivity of each parameter in BuildSheriff to the effectiveness of BuildSheriff? (Sec. 4.5)

Data Set. We used the 100 broken builds with exception failures and the 100 broken builds with assertion failures from **RQ3** of our empirical study in Sec. 2.1 as the data set for our evaluation. The ground truth has already been constructed during the analysis of **RQ3**.

Comparison Approaches. For **RQ4** and **RQ5**, we selected three state-of-the-art approaches: i) 1Frame, which triages crash reports using the top frame in stack traces. We selected it because it is practically used in Mozilla [17]. ii) 1File, which triages crash reports using the name of the source file in which the top frame is defined. We selected it as it achieved the highest triage precision in a recent empirical study [12]. iii) ReBucket, which triages crash reports based on the number of functions in two stack traces, the distance of those functions from the top frame, and the offset distance between the matched functions [15]. We selected it as it outperformed the triage method in Microsoft's Windows Error Reporting system. Moreover, given the results in **RQ3**, we developed one naive method 1Cluster, which simply puts all test failures into a single cluster.

Evaluation Metrics. To comprehensively evaluate the triage effectiveness, we used the number of builds whose failures were correctly triaged (referred to as *C.B.*) as an overall indicator of triage effectiveness, used the number of executions of all tests a developer needs to run (referred to as *T.E.*) and the number of test failures a developer needs to inspect (referred to as *T.F.*) in the two usage scenarios discussed in Sec. 3.5 to reflect the effort saving for a developer when using BuildSheriff, and used the number of missed root

Table 1: Effectiveness Comparisons to the State-of-the-Art on Exception Failures

Approach	*C.B.*	*T.E.1*	*T.F.1*	*T.E.2*	*T.F.2*	*M.R.*	*Purity*	*I.P.*	*FM.*	*Rand*	*Jac.*	*F.&M.*	*Ent.*	*C.E.*	*M.I.*	*V.I.*	*E.D.*	*B.Pre.*	*B.Rec.*	*B.FM.*
1Cluster	82	118	263	124	**124**	18	0.926	**1.000**	0.941	0.879	0.879	0.960	0.187	**0.000**	0.000	0.187	1.980	0.916	**1.000**	0.943
1File	64	108	348	109	291	8	0.966	0.854	0.865	0.754	0.734	0.893	0.076	0.493	0.111	0.570	2.980	0.964	0.835	0.849
1Frame	62	107	418	108	361	7	0.968	0.816	0.829	0.718	0.698	0.923	0.070	0.649	0.118	0.719	3.680	0.967	0.801	0.817
ReBucket	63	107	414	108	357	7	0.968	0.819	0.831	0.725	0.705	0.928	0.070	0.639	0.118	0.709	3.650	0.967	0.806	0.820
BuildSheriff	**94**	**104**	**130**	**105**	128	**4**	**0.984**	0.991	**0.981**	**0.964**	**0.945**	**0.986**	**0.042**	0.018	**0.145**	**0.060**	**1.280**	**0.981**	0.991	**0.981**

Table 2: Effectiveness Comparisons to the State-of-the-Art on Assertion Failures

Approach	*C.B.*	*T.E.1*	*T.F.1*	*T.E.2*	*T.F.2*	*M.R.*	*Purity*	*I.P.*	*FM.*	*Rand*	*Jac.*	*F.&M.*	*Ent.*	*C.E.*	*M.I.*	*V.I.*	*E.D.*	*B.Pre.*	*B.Rec.*	*B.FM.*
1Cluster	75	125	**148**	137	**137**	25	0.855	**1.000**	0.893	0.756	0.756	**0.997**	0.344	**0.000**	0.000	0.344	**1.480**	0.854	**1.000**	0.894
1File	54	120	218	130	218	20	0.876	0.878	0.819	0.603	0.581	0.941	0.288	0.362	0.056	0.650	2.290	0.875	0.868	0.811
1Frame	46	116	290	124	290	16	0.901	0.784	0.761	0.518	0.460	0.958	0.227	0.636	0.118	0.863	2.990	0.899	0.776	0.756
ReBucket	58	116	236	120	229	16	0.910	0.844	0.815	0.610	0.561	0.983	0.206	0.431	0.138	0.638	2.390	0.909	0.842	0.815
BuildSheriff	**89**	**101**	156	**101**	156	**1**	**0.988**	0.951	**0.955**	**0.915**	**0.806**	0.947	**0.032**	0.124	**0.313**	**0.155**	1.650	**0.988**	0.948	**0.954**

causes when a developer inspects one test failure per cluster (referred to as *M.R.*) to measure the impact of ineffective triage. Further, as the goal of BuildSheriff is to produce a set of clusters of test failures whose root cause is considered as the same, we need to compare the distance between the clusters generated by BuildSheriff and the ground-truth clusters manually constructed. To this end, we used all the five families of clustering evaluation metrics in Amigó et al. [4] as different families capture different perspectives of four clustering qualities, i.e., *cluster homogeneity* (a cluster should not mix test failures with a different root cause), *cluster completeness* (test failures with the same root cause should be grouped into the same cluster), *rag bag* (introducing noise into a noisy cluster is less harmful than introducing noise into a clean cluster), and *cluster size versus quantity* (a small error in a big cluster should be preferable to a large number of small errors in small clusters). We briefly list the five families as follows, and the detailed definition and the satisfaction level of the four qualities can be found in Amigó et al. [4].

- Metrics based on set matching: *Purity*, *Inverse Purity* (*I.P.*), and their combination *F-Measure* (*FM.*).
- Metrics based on counting pairs: *Rand Statistic* (*Rand*), *Jaccard Coefficient* (*Jac.*), and *Folkes and Mallows* (*F.&M.*).
- Metrics based on entropy: *Entropy* (*Ent.*), *Class Entropy* (*C.E.*), *Mutual Information* (*M.I.*), and *Variation of Information* (*V.I.*).
- Metric based on edit distance: *Edit Distance* (*E.D.*).
- Metrics based on BCubed: *BCubed Precision* (*B.Pre.*), *BCubed Recall* (*B.Rec.*), and their combination *BCubed F-Measure* (*B.FM.*).

For *Ent.*, *T.E.*, *T.F.*, *M.R.*, *C.E.*, *V.I.* and *E.D.*, the lower the better, and for the others, the higher the better.

4.2 Effectiveness Evaluation (RQ4)

Table 1 shows the results of 1Cluster, 1File, 1Frame, ReBucket and BuildSheriff with respect to the 20 effectiveness metrics on the 100 broken builds with exception failures. *T.E.* and *T.F.* for **Usage Scenario 1** are denoted as *T.E.1* and *T.F.1*, while *T.E.* and *T.F.* for **Usage Scenario 2** are denoted as *T.E.2* and *T.F.2*. The naive method 1Cluster achieved worse performance on 16 of the 20 metrics than BuildSheriff. Specifically, with 1Cluster in **Usage Scenario 1**, developers would inspect 263 of the 1,903 test failures and run 118 executions of all tests, which are 81.5% and 13.5% more than with BuildSheriff. In other words, BuildSheriff would save 81.5% of the test failure inspection effort and 13.5% of the test execution effort. With 1Cluster in **Usage Scenario 2**, developers would inspect 124 test failures and run 124 executions of all tests, which are 3.1% less and 18.1% more than with BuildSheriff. In other words, BuildSheriff would save 18.1% of the test execution effort at the cost of 3.1% more test failure inspection effort. Besides, developers would miss 18 of the 124 root causes when only inspecting one test failure per cluster with 1Cluster, which is 350.0% more than with BuildSheriff.

On the other hand, the state-of-the-art methods 1File, 1Frame and ReBucket had similar results on all the metrics except for *T.F.1*, *T.F.2*, *C.E.*, *V.I.* and *E.D.* on which 1File achieved better results, while BuildSheriff outperformed them on all the metrics. In particular, BuildSheriff significantly improved the best of the three state-of-the-art methods on all the metrics except for *T.E.1*, *T.E.2*, *Purity*, *F.&M.* and *B.Pre.*, i.e., by 46.9% on *C.B.*, 62.6% on *T.F.1*, 56.0% on *T.F.2*, 42.9% on *M.R.*, 16.0% on *I.P.*, 13.4% on *FM.*, 27.9% on *Rand*, 28.7% on *Jac.*, 40.0% on *Ent.*, 96.3% on *C.E.*, 22.9% on *M.I.*, 89.5% on *V.I.*, 57.0% on *E.D.*, 18.7% on *B.Rec.*, and 15.5% on *B.FM.*.

Table 2 shows the results on the 100 broken builds with assertion failures. Compared to 1Cluster, BuildSheriff achieved better performance on 13 of the 20 metrics. Although developers would inspect 148 and 137 of the 490 test failures with 1Cluster in **Usage Scenario 1** and **2**, which are 5.1% and 12.2% less than with BuildSheriff, developers would run 125 and 137 executions of all tests, which are 12.8% and 35.6% more than with BuildSheriff. In other words, BuildSheriff would save 12.8% and 35.6% of the test execution effort at the cost of 5.1% and 12.2% more test failure inspection effort. Besides, developers would miss 25 of the 137 root causes when only inspecting one test failure per cluster with 1Cluster, which is 2400.0% more than with BuildSheriff.

On the other hand, 1File and ReBucket achieved similar results but had better results than 1Frame on most of the metrics, while BuildSheriff outperformed 1File,1Frame and ReBucket on all the metrics except for *F.&M.*. In particular, BuildSheriff significantly improved the best of the three state-of-the-art methods on all the metrics except for *Purity*, *I.P.*, *F.&M.*, *B.Pre.* and *B.Rec.*, i.e., by 53.4% on *C.B.*, 12.9% on *T.E.1*, 28.4% on *T.F.1*, 15.8% on *T.E.2*, 28.4% on *T.F.2*, 93.8% on *M.R.*, 16.6% on *FM.*, 50.0% on *Rand*, 38.7% on *Jac.*, 84.5% on *Ent.*, 65.7% on *C.E.*, 126.8% on *M.I.*, 75.7% on *V.I.*, 27.9% on *E.D.*, and 17.1% on *B.FM.*.

These results demonstrate that i) the naive method would miss the highest number of root causes when developers only inspect one test failure per cluster although it could achieve a relatively high number of correctly triaged builds, and hence advanced failure

Table 3: Contributions of Each Strategy in BuildSheriff on Exception Failures

Approach	C.B.	T.E.1	T.F.1	T.E.2	T.F.2	M.R.	Purity	I.P.	FM.	Rand	Jac.	F.&M.	Ent.	C.E.	M.I.	V.I.	E.D.	B.Pre.	B.Rec.	B.FM.
1File	22	50	185	51	128	8	0.919	0.863	0.838	0.699	0.645	0.844	0.182	0.462	0.220	0.644	3.214	0.914	0.842	0.825
1Frame	21	49	215	50	158	7	0.924	0.825	0.808	0.664	0.614	0.887	0.166	0.611	0.236	0.777	3.929	0.921	0.807	0.798
ReBucket	22	49	212	50	155	7	0.936	0.846	0.835	0.706	0.658	0.908	0.142	0.540	0.260	0.683	3.571	0.933	0.827	0.824
S_e^2	31	**44**	112	**45**	111	**2**	0.974	0.865	0.874	0.796	0.744	0.922	0.060	0.433	0.342	0.493	2.643	0.973	0.856	0.868
Naive S_e^2	19	49	190	50	134	7	0.930	0.820	0.808	0.657	0.594	0.879	0.154	0.620	0.248	0.775	3.333	0.927	0.798	0.797
Simple S_e^2	26	45	115	46	114	3	0.962	0.845	0.854	0.747	0.688	0.897	0.084	0.494	0.318	0.578	2.738	0.961	0.829	0.843
S_e^3	30	48	73	50	70	6	0.927	0.962	0.923	0.832	0.797	0.929	0.168	0.104	0.234	0.272	1.786	0.922	0.953	0.918
S_e^2 + S_e^3	31	**44**	111	**45**	110	**2**	**0.988**	0.865	0.885	0.815	0.766	0.940	**0.024**	0.433	**0.378**	0.457	2.619	**0.988**	0.856	0.879
S_a^2	20	49	191	49	191	7	0.928	0.806	0.823	0.673	0.589	0.799	0.152	0.646	0.250	0.799	5.619	0.926	0.772	0.794
BuildSheriff	**38**	**44**	**70**	**45**	**68**	**2**	0.979	**0.979**	**0.968**	**0.947**	**0.900**	**0.987**	0.056	**0.043**	0.346	**0.099**	**1.619**	0.975	**0.979**	**0.969**

Table 4: Contributions of Each Strategy in BuildSheriff on Assertion Failures

Approach	C.B.	T.E.1	T.F.1	T.E.2	T.F.2	M.R.	Purity	I.P.	FM.	Rand	Jac.	F.&M.	Ent.	C.E.	M.I.	V.I.	E.D.	B.Pre.	B.Rec.	B.FM.
1File	17	64	**89**	74	**89**	20	0.718	0.942	0.753	0.439	0.376	**0.981**	0.655	0.139	0.128	0.794	**2.273**	0.715	0.940	0.754
1Frame	18	60	95	68	95	16	0.774	0.904	0.769	0.486	0.336	0.976	0.516	0.220	0.268	0.736	2.364	0.771	0.902	0.770
ReBucket	22	51	106	55	106	7	0.823	0.916	0.810	0.566	0.395	0.978	0.416	0.198	0.367	0.614	2.341	0.820	0.913	0.812
Naive S_a^2	24	49	115	49	115	5	**0.989**	0.779	0.832	0.619	0.186	0.868	**0.023**	0.524	**0.760**	0.547	2.818	**0.989**	0.776	0.832
Simple S_a^2	28	46	109	46	109	2	0.962	0.850	0.866	0.696	0.404	0.849	0.089	0.363	0.694	0.452	2.568	0.963	0.844	0.861
S_e^2	25	48	106	49	106	4	0.910	0.865	0.839	0.634	0.366	0.882	0.220	0.340	0.563	0.561	2.568	0.910	0.855	0.833
S_e^3	25	54	102	61	102	10	0.848	0.934	0.843	0.679	0.470	0.910	0.344	0.177	0.439	0.521	2.364	0.848	0.928	0.842
S_e^2 -> S_e^3	29	53	97	60	97	9	0.865	**0.962**	0.875	0.748	0.555	0.941	0.313	**0.126**	0.470	0.439	2.318	0.865	**0.952**	0.870
BuildSheriff	**33**	**45**	100	**45**	100	**1**	0.973	0.888	**0.898**	**0.808**	**0.559**	0.879	0.072	0.282	0.712	**0.353**	2.477	0.973	0.882	**0.895**

triage is needed; and ii) the state-of-the-art stack trace-based failure triage is not well applicable to triage exception and assertion failures in CI, while BuildSheriff is capable of achieving this goal.

We further analyzed the intersections among the correctly triaged builds by these methods. For the builds with exception failures, 82, 61, 58 and 59 of the correctly triaged builds by 1Cluster, 1File, 1Frame and ReBucket were also correctly triaged by BuildSheriff; and 8 of the correctly triaged builds by BuildSheriff were not correctly triaged by any other method. Similarly, for the builds with assertion failures, 66, 48, 41 and 52 of the correctly triaged builds by 1Cluster, 1File, 1Frame and ReBucket were also correctly triaged by BuildSheriff; and 13 of the correctly triaged builds by BuildSheriff were not correctly triaged by any other method.

Summary. BuildSheriff significantly outperformed the naive method and the best of the state-of-the-art methods on 13+ of the 20 metrics in triaging exception failures and assertion failures in CI builds. BuildSheriff achieved a test execution effort saving of up to 35.6% at the cost of up to 12.2% more test failure inspection effort when compared to 1Cluster, and achieved a test execution effort saving of up to 15.8% and a test failure inspection effort saving of up to 62.6% when compared to the state-of-the-art methods.

4.3 Efficiency Evaluation (RQ5)

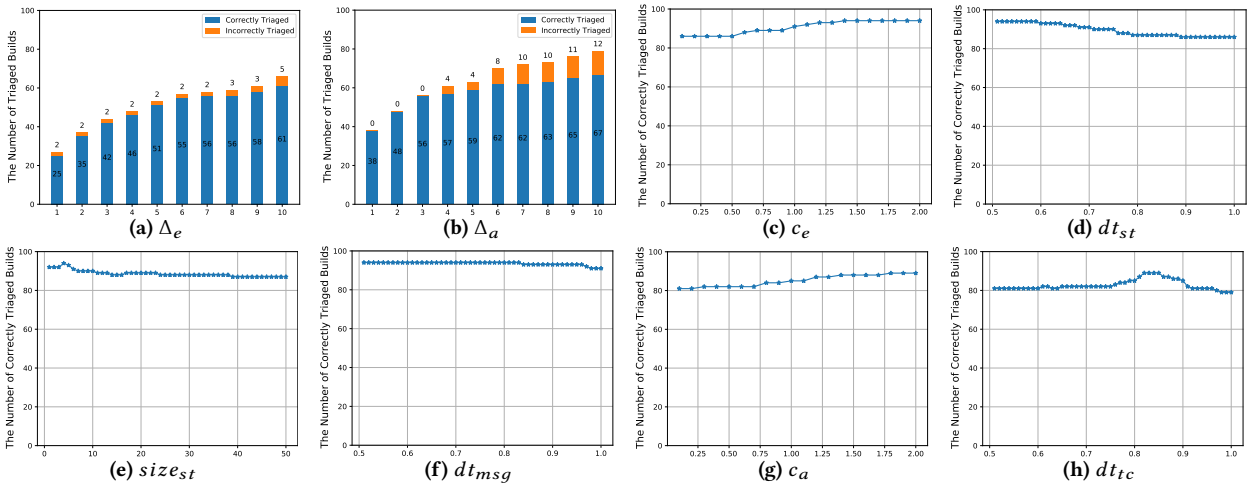
We analyzed the average end-to-end time overhead of the five triage methods over the 200 broken builds. 1Cluster, 1File, 1Frame, ReBucket and BuildSheriff respectively took 0.01, 0.10, 0.10, 0.13 and 1.61 seconds to triage a build. We excluded the time overhead of constructing the file dependency graph (which on average took 15.48 seconds for each project) from the time overhead of BuildSheriff as it was a one-time job for each project. Instead, BuildSheriff took 0.54 seconds to update the file dependency graph. While being the slowest due to code change analysis, BuildSheriff is still practical for CI.

Summary. BuildSheriff took 1.61 seconds to triage test failures in a CI build, which was acceptable for practical usage in CI.

4.4 Ablation Study (RQ6)

As BuildSheriff adopts three strategies for triaging exception failures and two strategies for triaging assertion failures, we broke down the broken builds with respect to the strategies that triaged them. 58 of the 100 broken builds with exception failures were triaged by $\mathbf{S}_e^1$, and 56 of them were correctly triaged; 28 were triaged by $\mathbf{S}_e^2$, and 25 of them were correctly triaged; and 14 were triaged by $\mathbf{S}_e^3$, and 13 of them were correctly triaged. 56 of the 100 broken builds with assertion failures were triaged by $\mathbf{S}_a^1$, and all of them were correctly triaged; and 44 were triaged by $\mathbf{S}_a^2$, and 33 of them were correctly triaged. These results demonstrate that each strategy contributes to the effectiveness of BuildSheriff. As $\mathbf{S}_e^1$ and $\mathbf{S}_a^1$ are not related to stack traces and thus can also be used in combination with 1File, 1Frame and ReBucket, we used the 42 broken builds with exception failures that were not triaged by $\mathbf{S}_e^1$ to further investigate the advantage of $\mathbf{S}_e^2$ and $\mathbf{S}_e^3$, and used the 44 broken builds with assertion failures that were not triaged by $\mathbf{S}_a^1$ to further investigate the advantage of $\mathbf{S}_a^2$.

Table 3 reports the results of 1File, 1Frame, ReBucket, BuildSheriff and its variants with respect to the 20 metrics on the 42 broken builds with exception failures. We can observe that if we only used $\mathbf{S}_e^2$ (i.e., the fifth row in Table 3), $\mathbf{S}_e^2$ still outperformed 1File, 1Frame and ReBucket on all metrics thanks to its consideration of code changes, but achieved worse results than a pipeline combination of $\mathbf{S}_e^2$ and $\mathbf{S}_e^3$ (i.e., the last row). If we gave the same weight to each frame in a stack trace (i.e., Naive $\mathbf{S}_e^2$ in the sixth row), Naive $\mathbf{S}_e^2$ had a degradation on all metrics, compared to $\mathbf{S}_e^2$. If we only distinguished whether a frame was changed or not without considering change impacts (i.e., Simple $\mathbf{S}_e^2$ in the seventh row), Simple $\mathbf{S}_e^2$ achieved better results than Naive $\mathbf{S}_e^2$ but had worse results than $\mathbf{S}_e^2$. These results show the advantage of considering code changes and their impacts during stack trace similarity measure. Besides, if we only used $\mathbf{S}_e^3$ (i.e., the eighth row), $\mathbf{S}_e^3$ achieved worse results than $\mathbf{S}_e^2$ and a pipeline combination of $\mathbf{S}_e^2$ and $\mathbf{S}_e^3$ on most of the metrics. If we adopted a weighted combination of $\mathbf{S}_e^2$ and $\mathbf{S}_e^3$ by equally weighting stack trace similarity and exception



(a) Δ_e (b) Δ_a (c) c_e (d) dt_{st}
(e) $size_{st}$ (f) dt_{msg} (g) c_a (h) dt_{tc}

Figure 8: Results of Parameter Sensitivity Analysis

message similarity (i.e., $\mathbf{S}_e^2$ + $\mathbf{S}_e^3$ in the ninth row), $\mathbf{S}_e^2$ + $\mathbf{S}_e^3$ suffered a degradation on most of the metrics. These results indicate the advantage of combining $\mathbf{S}_e^2$ and $\mathbf{S}_e^3$ in a pipeline. Further, if we adopted $\mathbf{S}_a^2$ from assertion failure triage (i.e., the tenth row), $\mathbf{S}_a^2$ had the worst results on most of the metrics. It demonstrates the rationality of not considering test code similarity for exception failure triage.

Table 4 reports the results of 1File, 1Frame, ReBucket, BuildSheriff and its variants with respect to the 20 metrics on the 44 broken builds with assertion failures. We can see that $\mathbf{S}_a^2$ (i.e., the last row in Table 4) outperformed 1File, 1Frame and ReBucket on all metrics except for *T.F.1*, *T.F.2*, *I.P.*, *F.&M.*, *C.E.*, *E.D.* and *B.Rec.*. It shows that stack traces provide a limited triage capability for assertion failure. If we gave the same weight to each test code token (i.e., Naive $\mathbf{S}_a^2$ in the fifth row), Naive $\mathbf{S}_a^2$ had a degradation on 16 of the 20 metrics, compared to $\mathbf{S}_a^2$. If we only distinguished whether a test code token was changed or not without considering change impacts (i.e., Simple $\mathbf{S}_a^2$ in the sixth row), Simple $\mathbf{S}_a^2$ achieved better results on 15 of the 20 metrics than Naive $\mathbf{S}_a^2$ but had worse results on all metrics than $\mathbf{S}_a^2$. These results demonstrate the advantage of considering code changes and their impacts during test case similarity measure. Moreover, if we adopted $\mathbf{S}_e^2$, $\mathbf{S}_e^3$ and a pipeline combination of $\mathbf{S}_e^2$ and $\mathbf{S}_e^3$ from exception failure triage (i.e., the seventh to ninth rows), they had worse results on 14 of the 20 metrics. It indicates a stronger capability of test code than stack traces and assertion messages for assertion failure triage.

Summary. Each triage strategy contributes to the effectiveness of BuildSheriff in triaging exception and assertion failures.

4.5 Parameter Sensitivity Analysis (RQ7)

Each triage strategy in BuildSheriff has some configurable parameters. We tuned these parameters in three ways. For Δ_e in $\mathbf{S}_e^1$ and Δ_a in $\mathbf{S}_a^1$, we configured them from 1 to 10 by a step of 1 to evaluate their impact on the triage results of $\mathbf{S}_e^1$ and $\mathbf{S}_a^1$. The results are reported in Fig. 8a and 8b, where the x-axis denotes the value of Δ_e and Δ_a, and the y-axis denotes the number of correctly/incorrectly triaged builds by $\mathbf{S}_e^1$ and $\mathbf{S}_a^1$. As Δ_e and Δ_a increased, both the number of correctly and incorrectly triaged builds increased. As $\mathbf{S}_e^1$ and $\mathbf{S}_a^1$ are desired to achieve a low number of incorrectly triaged builds so that other strategies can be tried, a small value of 7 and 3 was set to Δ_e and Δ_a.

For c_e, dt_{st} and $size_{st}$ in $\mathbf{S}_e^2$, dt_{msg} in $\mathbf{S}_e^3$, and c_a and dt_{tc} in $\mathbf{S}_a^2$, we configured c_e and c_a from 0.1 to 2 by a step of 0.1, dt_{st}, dt_{msg} and dt_{tc} from 0.51 to 1.0 by a step of 0.01, and $size_{st}$ from 1 to 50 by a step of 1 to evaluate their impact on the triage results of BuildSheriff. Here Δ_e and Δ_a was fixed to 7 and 3. Parameters in $\mathbf{S}_e^2$ and $\mathbf{S}_e^3$ were tuned together, and 2.5 million (i.e., $20 \times 50 \times 50 \times 50$) configurations were ran to obtain the optimal configuration. Similarly, 1000 (i.e., 20×50) configurations were ran to obtain the optimal configuration of the two parameters in $\mathbf{S}_a^2$. The results are shown in Fig. 8c-8h, where the x-axis denotes the parameter value, and the y-axis denotes the number of correctly triaged builds by BuildSheriff. As c_e and c_a increased, the number of correctly triaged builds increased and then stabilized. As dt_{st} and dt_{msg} increased, the number of correctly triaged builds decreased due to the increasingly strict cluster distance threshold. As $size_{st}$ increased, the number of correctly triaged builds first increased, then decreased and finally stabilized. As dt_{tc} increased, the number of correctly triaged builds was stable at first, then increased and finally decreased. The optimal configuration of c_e, dt_{st}, $size_{st}$, dt_{msg}, c_a and dt_{tc} is 1.7, 0.57, 4, 0.73, 1.8 and 0.82. As these parameters changed, the number of correctly triaged builds was always above 79, which was significantly higher than the achieved results of 1File, 1Frame and ReBucket. In that sense, the effectiveness of BuildSheriff is not very sensitive to these parameters.

For mDt_e in $\mathbf{S}_e^2$, we heuristically set it as one plus the maximum of the distances of the frames that reach changed files on $\mathcal{G}$ for all the 100 broken builds with exception failures. We heuristically set mDt_a in $\mathbf{S}_a^2$ in the same way. In this way, both mDt_e and mDt_a were configured to 6. We used such a heuristic way that the parameter configuration space is reduced, and frames and test code tokens that do not reach any changed file can still contribute to triage.

Note that in Sec. 4.2 and 4.4, we reported the results of the optimal configuration of BuildSheriff. For 1File, 2Frame and ReBucket, we also reported the results of their optimal configuration.

Summary. Overall, the sensitivity of the configurable parameters to the effectiveness of BuildSheriff is acceptable.

4.6 Discussion

Assumptions. As BuildSheriff is designed for test failure triage in CI builds, it can be used for software systems whose development

process follows the continuous integration practice, where developers frequently merge their code changes into a central repository and builds and tests then run. Therefore, if the continuous integration practice is not followed, or the continuous integration practice is followed but the software system has a small number of tests, BuildSheriff will become not applicable, or be less helpful.

Threats. One threat to our evaluation is that the size of our data set is not large. This is primarily due to the expensive effort in building the ground truth as we are not familiar with the business logic of open-source projects. We plan to collaborate with our industrial partners to deploy our tool into their CI to get developers' feedback. Besides, BuildSheriff is evaluated based on broken builds across heterogeneous projects. We plan to evaluate BuildSheriff within the build history of one project. In addition, two usage scenarios in Sec. 3.5 are considered in our evaluation, and there could be other usage scenarios. However, we believe the two usage scenarios are representative in practice. It is also hard to determine whether test execution effort or test failure inspection effort is more expensive, and thus we evaluate the triage effectiveness with both dimensions.

Limitations. First, BuildSheriff only triages test failures, but cannot directly pinpoint the root causes in source code which would be useful for developers to fix test failures. Second, some engineering effort is needed to extend BuildSheriff to support other programming languages, other CI services and other build tools by providing specific implementations for triage knowledge preparation. Third, the design of BuildSheriff does not consider flaky tests. If a flaky test is triaged into a cluster that has a different root cause from flakiness, and is selected as the representative test for manual inspection, the root cause of the cluster will not be fixed. Therefore, flaky tests could reduce the effort saving capability of BuildSheriff. To mitigate this problem, we can apply flaky test detection techniques (e.g., [7]) before BuildSheriff. Notice that there is no failure that is due to flakiness in our evaluation data set. Last, exception messages may be not available for some failed tests. In all the failed tests in 80,778 broken builds with exception failures, 89.0% of the failed tests contain exception messages. Without such messages, $\mathbf{S}_e^3$ becomes useless. In the extreme case, BuildSheriff without $\mathbf{S}_e^3$ still outperforms the existing methods (i.e., the fifth row in Table 3).

5 RELATED WORK

Stack Trace-Based Failure Triage. Brodie et al. [11] used the longest subsequence of common functions in stack traces as the indicator of stack trace similarity to identify re-occurring failures. To improve it, Brodie et al. [10] and Modani et al. [47] removed recursion and uninformative functions from stack traces before stack trace matching.

Bartz et al. [6] proposed a machine learning technique to find similar stack traces. However, this technique requires features (e.g., process name) that are often not available in test failures in CI.

Glerum et al. [23] proposed the crash bucketing algorithm in Windows Error Reporting (WER) by analyzing memory dumps collected from users. This technique requires knowledge (e.g., heap corruption) that are not available in test failures in CI. Kim et al. [39] proposed crash graphs to provide an aggregated view of the stack traces in the same bucket in WER. Differently, Koopaei and Hamou-Lhadj [40] modeled and abstracted the stack traces in the same bucket as an automaton. Dang et al. [15] improved the algorithm in [23] by measuring similarity between two stack traces. However, it needs to learn parameters' value from historical buckets.

Mozilla grouped crash reports by the top function in the stack trace, which was then improved by Dhaliwal et al. [17]. Lerch and Mezini [43] compared stack traces with TF-IDF to group bug reports.

These techniques use stack trace similarity to triage crash or bug reports. Differently, our work is focused on triaging test failures for each CI build. In this context, code changes in each build provide a good source of knowledge for triage, and thus we involve code changes in measuring stack trace and test code similarity. Moreover, these techniques are not applicable to assertion failures as such failures do not report any informative stack trace, but our work does.

To the best of our knowledge, one closely related test failure triage work was recently proposed by Golagha et al. [25]. It targeted test failures in CI. However, this technique was specifically designed for automotive industry, and thus the general, bug history and test case similarity features are not available in test failures in general CI.

Profiling-Based Failure Triage. Podgurski et al. [52] used profiles of failure executions and successful executions to group failures. Francis et al. [22] improved it by refining the initial classification of failures. Liu et al. [45] measured the failure similarity on dynamic slices. Given failing and passing executions, Liu et al. [44, 45] located bug location for each failure, and regarded two failures as similar if roughly the same bug location was suggested. DiGiuseppe and Jones [19] clustered failures with the semantic concepts that were expressed in the executed source code. Golagha et al. [26] clustered failed tests with execution profiles. However, they would impose large overhead due to profiling, which are not practical for CI [46].

Cui et al. [14] triaged crashes based on program semantics reconstructed from memory dumps. Pham et al. [51] used the symbolic execution tree to cluster failed tests. van Tonder et al. [65] used the approximated fixes to group crashes. These techniques aim to achieve semantic-aware crash triage, but would suffer scalability issue in CI.

Text-Based Failure Triage. The textual information (e.g., title and description) in bug reports are used to identify duplicate bug reports. Various techniques have been used to achieve this purpose, e.g., natural language processing [57, 68], machine learning [9, 35, 41, 58, 62], information retrieval [13, 32, 54, 61, 63, 64], and topic modeling [2, 3, 49]. However, for test failure triage in CI, there is no such descriptive text that can be utilized.

Crash Analysis. Other crash analysis methods include fault localization [27, 53, 70, 72, 74] and failure-inducing change identification [69, 71, 75], crash prioritization and assignment [38, 60], crash reproducing [5], and crash root cause classification [28, 29, 36, 56]. It is interesting to explore how they can practically work in CI.

6 CONCLUSIONS

In this paper, motivated by our large-scale study on test failures in CI, we propose a new change-aware approach, BuildSheriff, to triage test failures in each CI build. Our evaluation has indicated that BuildSheriff can significantly improve the state-of-the-art and be practically used in CI with a time overhead of 1.61 seconds for a build.

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