ChatUniTest: a ChatGPT-based automated unit test generation tool

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Abstract—Unit testing is a crucial, yet often tedious and time-consuming task. To relieve developers from this burden, automated unit test generation techniques are developed. Existing automated unit test generation tools, such as program-analysis-based tools like EvoSuite and Randoop, lack program comprehension, resulting in unit tests with poor readability and limited assertions. Language-model-based tools, such as AthenaTest and A3Test, have limitations in the generation of correct unit tests. In this paper, we introduce ChatUniTest, a ChatGPT-based automated unit test generation tool developed under the Generation-Validation-Repair framework. ChatUniTest generates tests by parsing the project, extracting essential information, and creating an adaptive focal context that includes the focal method and its dependencies within the pre-defined maximum prompt token limit. The context is incorporated into a prompt and subsequently submitted to ChatGPT. Once ChatGPT's response is received, ChatUniTest proceeds to extract the raw test from the response. It then validates the test and employs Rule-based Repair to fix syntactic and simple compile errors, followed by ChatGPT-based Repair to address challenging errors. Our rigorous evaluation demonstrates that ChatUniTest outperforms EvoSuite in branch and line coverage, surpasses AthenaTest and A3Test in focal method coverage, and effectively generates assertions while utilizing mock objects and reflection to achieve test objectives.

I. Introduction

Background. In today's world, where software is becoming more extensive and complex, even minor defects can result in significant financial losses and reputational damage to large companies. As a result, software testing are playing an even more critical role in the software development life cycle, ensuring software quality prior to product delivery. The fundamental and essential component of the software testing [1] is unit testing, which involves testing individual units of code. Unit testing helps developers identify defects and errors early in the development process, reducing the overall cost of development. Additionally, unit testing improves the maintainability and scalability of the software application, making it easier to modify and expand in the future. However, manually writing unit tests requires developers to put a lot of time and efforts, resulting it often ignored by developers.

To address this issue, automated unit test generations have been developed to relieve developers from writing simple but non-trivial unit tests. These tools are designed to produce unit tests that invoke Testing APIs in JUnit [2] and Mockito [3] to cover as much code under test as possible, so that most defects in the program are caught by unit tests. Automated unit test generation tools can be categorized into two directions: traditional unit test generation tool and deep learning unit test generation tool. EvoSuite [4] is a traditional unit test generation tool that uses evolutionary algorithms to generate new test cases and a fitness function to guide the search process, achieving high code coverage criteria like branch and line coverage. However, the unit tests generated by EvoSuite differ in essence from human-written tests, making them hard to read and understand. AthenaTest [5], a deep learning based tool, pretrains a BART model on English and code corpus and fine-tunes it on Methods2Test [6]. It attempts to directly translate source code to unit tests. A3Test [7] improves upon AthenaTest by incorporating assertion knowledge and verifying naming consistency and test signatures, achieving better results in terms of correctness and method coverage. However, these two stateof-the-art deep learning based tools have limitations, as they cannot repair a simple error by interacting with the deep learning model, leading to most generated tests being incorrect. The emergence of ChatGPT has the potential to transform the situation.

Motivation. ChatGPT demonstrated its capability in various domains, including generating unit tests. Our initial analysis revealed that ChatGPT can sometimes generate well-explained and understandable unit tests, but it frequently fails to complete the generation process. Furthermore, less than 20% of successful responses resulted in a correct unit test. To understand these issues, we examined the generation process and identified two critical limitations. Firstly, the limited token (e.g., 4096 tokens for GPT-3.5), which includes the prompt and completion, restricts ChatGPT from processing all relevant information required to generate effective response. Suggesting an adaptive generation of context, tailored to the test unit, could alleviate this limitation. Secondly, without appropriate compilers and test executors, ChatGPT is unable to validate the generated unit tests, leading to various

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errors, including "cannot find symbol" during compilation and "AssertionFailedError" during runtime. Some of these errors can be rectified by carrying out few rounds of consecutive validation and minor modification. Suggesting that a validation component as well as a repair component would significantly improve ChatGPT's effectiveness in generating unit tests.

Approach. Motivated by our initial analysis, we developed ChatUniTest¹ under the Generation-Validation-Repair framework. To address the first limitation, we define the test unit as a method and designed an adaptive focal context generation mechanism, which generates a context containing as much as necessary information for the focal method, while leaving enough space for Chat-GPT to produce complete responses. To tackle the second limitation, we implemented a validation component and a repair component. The validation component includes a parser, compiler, and test executor. The repair component consists of rule-based repair and ChatGPT-based repair. Rule-based repair addresses simple errors such as syntax errors and missing import statements. If rule-based repair fails, ChatUniTest resorts to ChatGPT-based repair. It constructs a prompt with an error message, incorrect unit test, and adaptive focal context to obtain the corrected unit test from ChatGPT. If a test remains unfixed after several validation and repair rounds, it is marked as deprecated.

Evaluation Results. In the experiment, we aimed to validate ChatUniTest's effectiveness, which generated correct tests in 30% of attempts. It outperformed EvoSuite in branch coverage for 7 out of 10 projects and line coverage for 8 out of 10 projects. ChatUniTest also demonstrated superior performance when compared to AthenaTest, achieving a result equivalent to A3Test in terms of the correct test percentage. Moreover, ChatUniTest produced an overwhelmingly positive outcome in terms of focal method coverage, reaching 79.67%, when compared to both AthenaTest (43.75%) and A3Test (46.80%). ChatUniTest also excelled in comparison to AthenaTest and A3Test on 16 out of 18 methods in the NumberUtils class in the Defects4J Lang-1-f revision, showcasing significant advantages in terms of method line coverage as well.

Contributions. In this paper, we introduce ChatUniTest, a ChatGPT-based automated unit test generation tool. ChatUniTest offers the following noteworthy contributions:

- ChatUniTest is the first ChatGPT-based automated unit test generation tool, outperforming EvoSuite in terms of branch coverage and line coverage, while also surpassing AthenaTest and A3Test in terms of focal method coverage and method line coverage.
- ChatUniTest introduces an Adaptive Focal Context Generation algorithm, capable of adaptively generat-

 $^1\mathrm{We}$ have released the artifact at https://github.com/ZJU-ACES-ISE/ChatUniTest

- ing prompts with the required context, while staying within the maximum prompt token limit, thereby avoiding truncated responses from ChatGPT.
- ChatUniTest can effectively repairs syntactic errors and simple compile errors in unit tests utilizing its rule-based repair component. Furthermore, it is capable of resolving approximately 50% of challenging errors by interacting with ChatGPT within the ChatGPT-based repair component.

II. RELATED WORK

Program-analysis-based Unit Test Generation

Various program analysis techniques are used to generate unit test automatically, such as random testing, search-based testing, and symbolic execution. For the tools fallen in this type, EvoSuite and Randoop are the most-widely used tools among them. EvoSuite [4] generates initial individuals randomly and applies an evolutionary algorithm to select, mutate, and combine test cases based on their fitness values. This leads to the evolution of test suites towards better performance. It is likely to achieve high branch and line coverage, but lacks the ability to generate meaningful test cases, such as variable names, test names and assertions, resulting in generated unit tests with poor understandability and maintainability.

Randoop [8] randomly selects and invokes methods from the class under test, along with its dependent classes. It builds sequences of method calls, incorporating feedback to guide the test generation process. However, it can only produce simple unit tests with limited code coverage, cannot handle complex dependencies, and its generated tests are not easy to read, understand or maintain, similar to EvoSuite.

Language-model-based Unit Test Generation

The introduction of Transformer [9] has been a game-changer in the field of natural language processing (NLP) and programming language processing (PLP) [10]–[15]. Extensive research on unit test generation has been carried out on Transformer-based language models.

AthenaTest [5] generates human-written unit tests from source code by treating unit test generation as a translation task. It generates a focal context for each focal method and attempts to translate it into human-written unit tests by fine-tuning its model on the Methods2Test [6] dataset. However, less than 20% of the generated unit tests are correct. To address this problem, A3Test [7] improves pretraining by using a PLBART model and fine-tuning it with Methods2Test. By verifying naming consistency and ensuring that test signatures match assertion knowledge, A3Test-generated unit tests achieve better coverage and correctness than AthenaTest. However, both models fail to correct fundamental errors in the generated unit tests.

TESTPILOT [16] automatically generates unit tests for JavaScript programs using Codex [17], without additional training or few-shot learning. It uses function signatures,

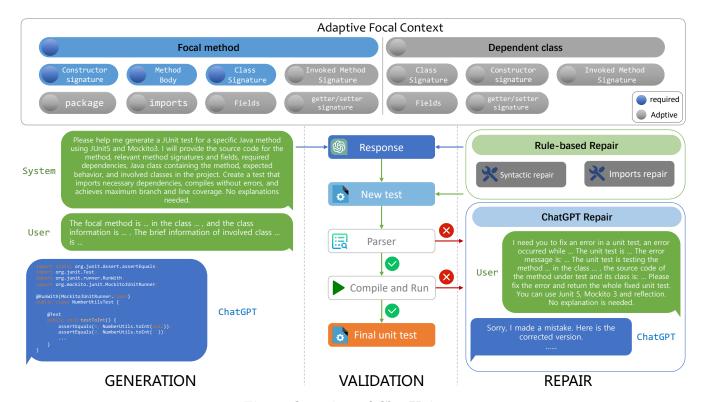


Fig. 1: Overview of ChatUniTest

implementation, and usage examples extracted from documentation. TESTPILOT adds the test and error message to the prompt to fix failing tests. However, the usage of documentation makes it insuitable to undocumented or less-documented programs.

Except for the above end-to-end solutions, recent studies [18], [19] also investigate integrate LLMs with programanalysis-based test generation, especially for test input generation.

III. Approach

As mentioned previously, ChatGPT encounters two limitations when generating a unit test: the token limit and the absence of validation and repair components. This section will outline the design of ChatUniTest and explain how it overcomes these limitations, thereby facilitating the automated generation of high-quality unit tests with an elevated success rate.

Figure 1 provides an overview of ChatUniTest, which utilizes the Generation-Validation-Repair framework. To enable parallelization, ChatUniTest first requires some preprocessing, including analyzing projects, parsing Java file, and extracting the necessary information for use in the generation process. The focal method needs to pass through the following components to generate a correct unit test:

• Generation During the generation phase, ChatUniTest generates an adaptive focal context based on the focal method and pre-defined maximum prompt

- token limit. It then renders the context into a prompt and obtains a response from ChatGPT.
- Validation In the validation phase, ChatUniTest extracts a test from ChatGPT's response and checks it for any syntactic errors, compilation errors, or runtime errors.
- Repair During the repair phase, ChatUniTest attempts to fix simple errors in the unit test using rule-based repair. If the error persists, ChatUniTest resorts to ChatGPT-based repair to resolve it.

Preprocessing

In order to streamline and parallelize the entire process, preprocessing the projects under test is necessary. ChatUniTest begins by traversing the project folder and locating all the java files, after which it parses each class file into an Abstract Syntax Tree (AST). While navigating the AST, ChatUniTest collects the information at two levels: class and method. Class level information includes the package, imports, class signature, fields, and method signatures. Method level information includes method body, field access, getter/setter invocation, dependent class name, and method invocation (e.g., max(byte, byte, byte)), which is used to identify a unique method when there are several methods with the same name.

Generation

The purpose of the generation component is to generate an adaptive focal context and integrate it into a prompt while ensuring that the prompt length remains under the

TABLE I: Abbreviation Table

Abbr.	Explaination
FC	focal class
FM	focal method
DC	dependent class
$_{ m IM}$	invoked method
body	source code
sig	signatures
ms	method signature
flds	fields
gs	getter and setter signatures
ns	namespace, including package and imports
ctor	constructor signature
ctx	context
dep	dependency
hasDep	has dependency
maxPrtLen	maximum prompt token limit
prtTemp	prompt template

limit of maximum prompt tokens, allowing ChatGPT sufficient space to generate complete responses. We propose an adaptive focal context generation algorithm, presented in Algorithm 1, with abbreviations provided in Table I for clarity. ChatUniTest first verifies if the required context can be rendered into a prompt that satisfies the maximum prompt token limit. If it fails to do so, ChatUniTest terminates the process, as missing information in the required context would result in invalid unit tests. ChatUniTest then attempts to add more information to the current context in order of importance, while verifying that each new addition complies with the maximum prompt token limit. If the method has dependencies, the dependent class signature, dependent class constructor, and invoked method signature are added to the context to provide a better understanding of how to instantiate a dependent class, invoke its method without compilation errors, and provide the return type information. If the method has no dependencies, ChatUniTest considers adding the method signature invoked by the focal method, as it provides parameter type and return type information. If the token limit allows, ChatUniTest then attempts to add all method signatures inside the focal class to the context to provide a comprehensive understanding of the method's role and purpose.

Once the adaptive focal context is generated, ChatUniTest renders it into a prompt, using the prompt template presented in Figure 2 if the context has no dependent class information, and the template in Figure 3 if it does. The successfully generated prompt complies with the maximum prompt token limit and is sent to ChatGPT through OpenAI's API.

Algorithm 1: Adaptive Focal Context Generation

```
1 Function AdaptiveFocalContextGeneration:
        Input: FC, FM, DC, IM<sub>sig</sub>, hasDep, maxPrtLen,
                    prtTemp, prtTemp<sub>dep</sub>
        Output: prompt
        context \leftarrow FC_{sig} + FC_{ctor} + FM_{body}
 2
        if useFlds then
 3
            context \leftarrow context + FC_{flds} + FC_{gs}
 4
        tokens ← TokenCount (prtTemp, context)
        if tokens > maxPrtLen then
 6
            Throw "Error: required context not satisfied!"
 7
        contextNew \leftarrow context + FC_{ns}
 8
        tokens ← TokenCount (prtTemp, contextNew)
 9
10
        if tokens < maxPrtLen then
            context \leftarrow contextNew
11
        else
12
            prompt ← GeneratePrompt (prtTemp, context)
13
            return prompt
14
        if hasDep then
15
16
            contextNew \leftarrow context + DC_{sig} + DC_{ctor} + IM_{sig}
            tokens \leftarrow TokenCount (prtTemp_{dep}, contextNew)
17
            if \ \ tokens < maxPrtLen \ \mathbf{then}
18
                context \leftarrow contextNew
19
            prompt ← GeneratePrompt (prtTempdep, context)
20
21
        else
22
            contextNew \leftarrow context + IM_{sig}
            tokens ← TokenCount (prtTemp, contextNew)
23
            if tokens < maxPrtLen then
24
                context \leftarrow contextNew
25
                contextNew \leftarrow context + FC_{ms}
26
                tokens \leftarrow \texttt{TokenCount} \; (\texttt{prtTemp}, \, \texttt{contextNew})
27
                if tokens < maxPrtLen then
28
                    \mathsf{context} \leftarrow \mathsf{contextNew}
29
            prompt ← GeneratePrompt (prtTemp, context)
30
        return prompt
31
```

```
Please help me generate a whole JUnit test for a focal
          method in a focal class.
          I will provide the following information:
          1. Required dependencies to import.
          2. The focal class signature.
          3. Source code of the focal method.
System
          4. Signatures of other methods and fields in the class.
          I need you to create a whole unit test using JUnit 4 and
          Mockito 3, ensuring optimal branch and line coverage. The
          test should include necessary imports for JUnit 4 and
          Mockito 3, compile without errors, and use reflection to
          invoke private methods. No additional explanations
          The focal method is method_name in focal class
 User
          class_name, the information is focal_method_context .
```

Fig. 2: Prompt for focal method without dependency

Validation

After receiving a response from ChatGPT, ChatUniTest extracts and validates the test while selecting a different repair component if any errors are detected during the validation process.

Extract: In our preliminary analysis, we discovered that ChatGPT occasionally fails to satisfy all the re-

```
Please help me generate a whole Junit test for a focal method in
            I will provide the following information of the focal method:
             1. Required dependencies to import.
               The focal class signature.
               Source code of the focal method.

    Signatures of other methods and fields in the class.
    Will provide following brief information if the focal method

System
            has dependencies:

    Signatures of dependent classes.

            2. Signatures of dependent methods and fields in the dependent
            I need you to create a whole unit test using {\tt JUnit}\ {\tt 4} and {\tt Mockito}
            3, ensuring optimal branch and line coverage. The whole test
             should include necessary imports for JUnit 4 and Mockito 3
            compile without errors, and use reflection to invoke private
             methods. No additional explanations required.
            The focal method is method name in the focal class
             class_name, and their information is focal_method_context
 User
             The brief information of dependent class class_name is
             dependent_class_context. The brief information of ...
```

Fig. 3: Prompt for focal method with dependency

quirements outlined in the prompt, even when explicitly instructed with "no explanation needed". Consequently, we developed two generalized approaches for extracting tests from responses. Tests are typically provided in two formats: delimited by triple backticks or as plain code without a delimiter. For the former format, ChatUniTest employs regular expressions to identify strings enclosed within triple backticks and filters out code snippets lacking the "@Test" annotation. For the latter format, ChatUniTest locates the line containing the keyword "public *Test" in the response and attempts to determine the test boundary by verifying that the first character in a line is valid in Java syntax. If ChatUniTest fails to extract any test from ChatGPT's response, the entire process is terminated immediately.

Parse: Upon successful test extraction, ChatUniTest utilizes a Java parser to verify the test's syntax. If a syntactic error is detected at this stage, ChatUniTest forwards the test to the rule-based repair component for correction.

Compile and run: In this step, ChatUniTest compiles and executes the test. If the test fails to compile or encounters errors during execution, it proceeds to the repair process. A test is considered passed only if it is free from syntax errors, compiles successfully, runs without errors.

Repair

```
I need you to fix an error in a unit test, an error occurred while error_type.
The unit test is unit_test.
The error message is error_message.
The unit test is testing the method_name in the class class_name, the source code of the method under test and its class is: focal_method_context.
```

Fig. 4: Prompt for repairing error

Throughout this process, ChatUniTest strives to fix any errors detected during validation. The repair component is divided into two parts: rule-based repair and ChatGPT-based repair. The rule-based repair component focuses on correcting simple and common errors without requiring any token usage, while the ChatGPT-based repair component targets more complex and challenging errors that require modifications to the code structure. After successfully repairing an error through this component, the test is sent to the validation component for further verification of its correctness.

Syntactic repair: When extracting tests from Chat-GPT's response, syntactic errors may occur due to the 4096 tokens limit being exceeded, resulting in truncated tests. In such cases, ChatUniTest implements a syntactic repair method. Initially, it identifies the last semicolon or closing brace and adds the necessary closing braces to ensure that the number of opening braces is balanced. ChatUniTest then verifies the syntactic correctness of the test. If the first approach fails, ChatUniTest attempts to remove the last test by locating the "@Test" annotation, truncating the code before the annotation, and then adding closing braces to complete the test structure. If the repair process fails or there are no tests left after the removal, the entire process is terminated.

Imports repair: A substantial number of raw tests obtained from ChatGPT may encounter compilation errors such as "cannot find symbol". To address this issue, ChatUniTest performs import repairs by ensuring that the dependencies in the focal class are present in the test.

ChatGPT repair: If rule-based repair is unable to correct an error, ChatUniTest resorts to ChatGPT-based repair. ChatUniTest extracts information about the error type and message, combined with focal method context, and generates a prompt by rendering the information into a prompt template, as shown in Figure 4. However, some error messages can be lengthy and verbose, leading to prompts that exceed the maximum prompt token limit. In such cases, ChatUniTest attempts to truncate the error message to ensure that the prompt is within the limit. If the prompt still exceeds the limit or if a test cannot be fixed after six rounds, the entire process is terminated.

IV. Experiment Design

In the experiment, the ChatUniTest will be configured to generate unit tests for each focal method within six attempts, while restricting the maximum number of rounds to six. If the prompt token limit exceeded 2700, the attempt will be aborted. Additionally, if an attempt fails to produce a passing test within six rounds, it will be deprecated. The temperature of the GPT-3.5-turobo model will be set to 0.5, enabling it to generate diverse unit tests.

To evaluate the effectiveness of ChatUniTest, we formulate four research questions:

TABLE II: Projects dataset

Project	Abbr.	Domain	Version	Trained	# Methods
Commons-Lang [20]	Lang	Utility	3.12.0	yes	3018
Commons-Cli [21]	Cli	Cmd-line interface	1.5.0	yes	250
Commons-Csv [22]	Csv	Data processing	1.10.0	yes	209
Gson $[23]$	Gson	Serialization	2.10.1	yes	660
Jfreechart [24]	Chart	Visualization	1.5.4	yes	8340
Ecommerce-microservice-backend-app [25]	Ecommerce	Microservices	695a6d4	no	316
Datafaker [26]	Datafaker	Data generation	1.9.0	no	1766
Flink-kubernetes-operator [27]	Flink-k8s-opr	Cloud computing	1.4.0	no	844
Binance-connector-java [28]	Binance-conn	API wrapper	2.0.0	no	474
Event-ruler [29]	Event-ruler	Event Engine	1.2.1	no	485
Total					16362

RQ1: How is the quality of the generated unit test cases?

To address this question, we will employ ChatUniTest to automatically generate unit tests for ten Java projects listed in Table II. We will measure test coverage using Cobertura [30] and Jacoco [31]. These projects not only encompass a wide range of domains, such as utility, middleware, and distributed computing platforms, but also cover various Java versions, including Java 11 and Java 17. Notably, five selected projects were excluded from ChatGPT's training data because they were created after December 1, 2021, to prevent possible data leakage.

In evaluating the quality of the generated test cases, we considered several factors, such as:

- Syntactic Correctness Syntactic correctness refers to whether the test code adheres to Java syntax rules, which we will verify using a Java parser.
- Compile Correctness Compile correctness will be deemed if the test does not produce any errors during compilation using the Java Compiler.
- Passing We will use JUnit as the test executor to verify if a test is passing, meaning that it does not produce any runtime errors during execution.
- Testing APIs invocations Well-written unit test cases should verify the expected behavior of MUT by invoking Testing APIs. For instance, test cases should use JUnit Assert APIs (e.g. assertEqual(), assertTrue()) to check the return value of MUT, and Mockito Framework APIs (e.g., mock(), verify(), when()) to simulate the behavior of an external dependency.
- Correct We define a test as correct if it is syntactically accurate, compiles and runs without errors, invokes the method under test, contains assertions, and enables the target code to pass the test.

RQ2: How does the performance of ChatUniTest compare against EvoSuite, AthenaTest, and A3Test?

In this research question, we compare ChatUniTest against three alternative approaches: EvoSuite (programanalysis-based test generation), AthenaTest (language-

model-based test generation) and A3Test (language-model-based test generation). We evaluate the comparison between ChatUniTest and EvoSuite on ten Java projects (see Table II) based on branch and line coverage.

For the comparison among ChatUniTest, AthenaTest, A3Test, we use the Defects4J dataset. Specifically, we first compare their method line coverage on class NumberUtils in Defects4J Lang-1-f revision. Then, we will compare their correct test cases pertentage and focal method coverage across entire Defects4J dataset.

- Correct Test Percentage The correct test percentage represents the percentage of correctly formulated tests in all attempts.
- Focal Method Coverage The focal method coverage denotes the percentage of focal methods that were covered during the generation of unit tests. A focal method is considered covered if it was correctly tested within the given attempt.

RQ3: What are the contributions of different components of ChatUniTest?

In this research question, we divide ChatUniTest into three components and assess their contributions to the overall test cases separately. We evaluate their contributions based on the ratio of correct tests and method code coverage.

RQ4: How much does it cost to generate unit tests?

Our objective for this research question is to gain an insight into the cost incurred by using ChatUniTest. The experiment will evaluate the token cost per method across different projects. We will also explore the distribution of prompt tokens, completion tokens during generation and repair process. Note that at present, model gpt-3.5-turbo charges \$0.002 for every 1000 tokens. [32]

V. EVALUATION

In this section, we present the experimental results and provide answers to the research questions posed in this study.

TABLE III: Performance of ChatUniTest on 10 Java projects: outcomes of Test Case Generation Attempts

Projects	Methods	Attempts	Aborted	SyntaxError	CompileError	RuntimeError	Passed	Correct
Lang	3018	18108	66	1112 (6.16%)	3952 (21.90%)	6755 (37.44%)	6220 (34.48%)	6118 (33.91%)
Cli	250	1500	0	11~(0.73%)	360 (24.00%)	521 (34.73%)	539 (35.93%)	520 (34.67%)
Csv	209	1254	6	11~(0.88%)	363 (29.09%)	346 (27.72%)	393 (31.49%)	373 (29.89%)
Gson	660	3960	150	54 (1.42%)	1487 (39.03%)	1065~(27.95%)	1080 (28.35%)	1047 (27.48%)
Chart	8340	50040	42	613~(1.23%)	$17843 \ (35.69\%)$	14100~(28.20%)	$17517 \ (35.04\%)$	17076 (34.15%)
Ecommerce	316	1896	6	40 (2.12%)	958 (50.69%)	315 (16.67%)	581 (30.74%)	574 (30.37%)
Datafaker	1766	10596	6	47~(0.44%)	$7754 \ (73.22\%)$	$1562\ (14.75\%)$	$1099 \ (10.38\%)$	1082 (10.22%)
Flink-k8s-opr	844	5064	12	212~(4.20%)	3278 (64.89%)	$629\ (12.45\%)$	938 (18.57%)	871 (17.24%)
Binance-conn	474	2844	6	19~(0.67%)	1205 (42.46%)	$419 \ (14.76\%)$	$1155 \ (40.70\%)$	1019 (35.91%)
Event-ruler	485	2910	0	17~(0.58%)	1514~(52.03%)	689~(23.68%)	686~(23.57%)	$662\ (22.75\%)$
Total	16362	98172	294	2136 (2.18%)	38714 (39.55%)	26401 (26.97%)	30208 (30.86%)	29342 (29.98%)

RQ1: How is the quality of the generated Test Cases?

In Table III, we present the performance of ChatUniTest on 10 Java projects, wherein it processed a total of 16,362 methods and made 98,172 unit test generation attempts. Out of these attempts, 294 were aborted due to exceeding the maximum prompt token limit.

Regarding syntax errors, 2.18% of the attempts encountered this issue. The highest percentage of syntax errors was observed in the Lang project (6.16%). Upon manual investigation of the results, we found that the most common reason for these errors was the generation of overly lengthy tests, which were subsequently truncated and cannot be repaired by syntactic repair component.

Compile errors were encountered in 39.55% of the unit test generation attempts. The highest percentage of compile errors was observed in the Datafaker project (73.22%). The most common types of errors were "cannot find symbol" or "incompatible types", primarily caused by ChatUniTest generating non-existing methods or classes, or making mistakes in their usage.

In terms of runtime errors, the Lang project had the highest percentage (37.44%). The most common types of errors were "org.opentest4j.AssertionFailedError: expected: ... but was: ..." and "cannot invoke ... because ... is null". These errors were primarily due to the misuse of assertions or reflection.

As for passed and correct test cases, 30.86% of the attempts were passed, with 29.98% of them being correct. This demonstrates the potential of ChatUniTest in general, as it exhibits good performance across most of the projects regardless of their size or Java version. Additionally, ChatUniTest has the ability to utilize mock objects or reflection to achieve the desired test objectives. This overall performance suggests that ChatUniTest can be a valuable asset in generating test cases for a wide range of Java projects.

The utilization of TestAPIs is crucial for ensuring the quality of unit tests. To investigate TestAPI usage in unit tests generated by ChatUniTest, we examined all successfully executed test files and recorded their TestAPI invocations. Figure 5 presents the distribution of asser-

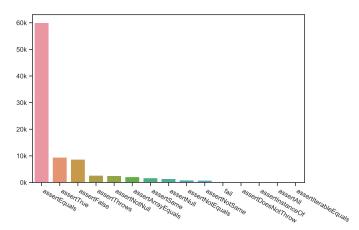


Fig. 5: Distribution of assertion invocations in passed tests

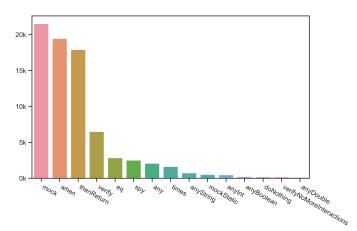


Fig. 6: Distribution of mock invocations in passed tests

tions, featuring the top 15 non-zero invoked assertion types. ChatUniTest can successfully invoke all 15 types of assertions, with an average of 3 assertions per unit test. Additionally, Figure 6 exhibits the distribution of mock invocations, highlighting the top 15 out of 34 types of invoked mock APIs. The most commonly used APIs include mock(), when(), and thenReturn(), while ChatUniTest is also capable of successfully invoking less frequently used APIs such as doNothing() and verifyNoMor-

eInteractions(). These findings emphasize that the unit tests generated by ChatUniTest are abundant in TestAPI invocations, with ChatUniTest effectively utilizing both assertions and mocks to improve test quality.

Answer to RQ 1

ChatUniTest achieved a 30.86% pass rate and 29.98% correct test cases in 97,878 successful attempts. The passed tests are rich in both quantity and variety of assertions and mocks, averaging three assertions per unit test. This demonstrates ChatUniTest's capability in generating high-quality unit tests.

RQ2: How does the performance of ChatUniTest compare against EvoSuite, AthenaTest, and A3Test?

TABLE IV: Branch and line coverage comparison of EvoSuite and ChatUniTest on 10 Java projects

Projects	Branch Coverage		Line Coverage		
	EvoSuite	Our	EvoSuite	Our	
Lang	84.92%	94.70%	84.71%	91.94%	
Cli	90.90%	96.36%	90.93%	93.52 %	
Csv	75.87%	84.09%	70.28%	86.61%	
Gson	59.23%	83.88%	61.53%	86.80%	
Chart	87.67%	$\pmb{88.27\%}$	85.90%	84.03%	
Ecommerce	100%	100%	89.58%	96.35%	
Datafaker	$\boldsymbol{91.12\%}$	89.76%	58.55%	86.07%	
Flink-k8s-opr	89.72 %	78.76%	87.14%	83.02%	
Binnance-conn	98.72%	97.17%	87.59%	97.87%	
Event-ruler	87.78%	93.14 %	84.02%	87.40%	
Average	86.59%	90.61%	80.02%	89.36%	

In Table IV, we compare the branch and line coverage of ChatUniTest and EvoSuite on 10 different Java projects. From the table, we can observe that ChatUniTest generally outperforms EvoSuite in terms of branch coverage for the majority of the projects. For example, in the Cli project, ChatUniTest achieves higher both branch and line coverage (96.36% and 93.52%, respectively) compared to EvoSuite (90.90% and 90.93%, respectively). Similar trends can be seen in other projects, such as Csv, Gson, and Event.

However, there are cases where EvoSuite surpasses ChatUniTest in terms of branch or line coverage, albeit with minor advantages. For instance, in the Datafaker project, EvoSuite achieves a higher branch coverage of 91.12% compared to ChatUniTest's 89.76%. Additionally, in the Chart project, EvoSuite has a higher line coverage of 85.90% compared to ChatUniTest's 84.03%.

Despite these exceptions, ChatUniTest outperforms EvoSuite in terms of line coverage across most projects. On average, ChatUniTest demonstrates an advantage in both branch and line coverage, with average branch coverage of 90.61% compared to EvoSuite's 86.59%, and average line coverage of 89.36% compared to EvoSuite's 80.02%. This consistency in ChatUniTest's results highlights its reliability and effectiveness as a unit test generation tool.

In Table V, we present an evaluation of the method line coverage performance of AthenaTest, A3Test, and ChatUniTest on the NumberUtils class in the Defects4J Lang-1-f revision. The data for AthenaTest and A3Test in the table is retrived from the results presented in A3Test [7], while the data for ChatUniTest is obtained from our experiments. From the table, it is evident that ChatUniTest generally outperforms both AthenaTest and A3Test in terms of method line coverage on 15 out of 17 methods. Notably, in the toInt(String, int) method, ChatUniTest achieves an impressive coverage of 20.0% (75 lines), while AthenaTest and A3Test reach coverage levels of 6.1% (23 lines) and 6.4% (24 lines), respectively. However, there are two methods, createLong(String) and min(int, int, int), where A3Test outperforms ChatUniTest.

In Table VI, we present an evaluation of the performance of the three tools on the Defects4J dataset, focusing on the percentage of correct test cases and the focal method coverage. We compare the three tools on the Defects4J dataset. The data for AthenaTest and A3Test in the table is adapted from A3Test [7] as well. From the table, we can observe that ChatUniTest consistently outperforms both A3Test and AthenaTest in terms of the percentage of correct test cases for all projects except Lang. With respect to focal method coverage, ChatUniTest outperforms both AthenaTest and A3Test across all five projects.

The utilization of TestAPIs is crucial for ensuring the quality of unit tests. To investigate TestAPI usage in unit tests generated by ChatUniTest, we examined all successfully executed test files and recorded their TestAPI invocations. Figure 5 presents the distribution of assertions, featuring the top 15 non-zero invoked assertion types. ChatUniTest can successfully invoke all 15 types of assertions, with an average of 3 assertions per unit test. Additionally, Figure 6 exhibits the distribution of mock invocations, highlighting the top 15 out of 34 types of invoked mock APIs. The most commonly used APIs include mock(), when(), and thenReturn(), while ChatUniTest is also capable of successfully invoking less frequently used APIs such as doNothing() and verifyNoMoreInteractions(). These findings emphasize that the unit tests generated by ChatUniTest are abundant in TestAPI invocations, with ChatUniTest effectively utilizing both assertions and mocks to improve test quality.

TABLE V: Method line coverage comparison, compare to AthenaTest and A3Test on class NumberUtils in Defects4J Lang-1-f

Focal Method	AthenaTest	A3Test	ChatUniTest
toInt(String, int)	23 (6.1%)	24 (6.4%)	75 (20.0%)
toLong(String, long)	20 (5.3%)	21 (5.6%)	31~(8.3%)
toFloat(String, float)	22 (5.9%)	21 (5.6%)	25~(6.7%)
toDouble(String, double)	$20 \ (5.3\%)$	21 (5.6%)	26~(6.9%)
toByte(String, byte)	23 (6.1%)	23 (6.1%)	25~(6.7%)
toShort(String, short)	22 (5.9%)	23 (6.1%)	25~(6.7%)
createFloat(String)	$20 \ (5.3\%)$	21 (5.6%)	23~(6.1%)
createDouble(String)	21~(5.6%)	21 (5.6%)	23~(6.1%)
createInteger(String)	21 (5.6%)	-	23~(6.1%)
createLong(String)	21~(5.6%)	23 (6.1%)	21 (5.6%)
createBigInteger(String)	20 (5.3%)	28 (7.5%)	39~(10.4%)
createBigDecimal(String)	22 (5.9%)	22 (5.9%)	34~(9.1%)
$\min(\log[])$	22 (5.9%)	22 (5.9%)	37~(9.9%)
min(int, int, int)	22 (5.9%)	25~(6.7%)	23 (6.1%)
$\max(\text{float}[])$	22 (5.8%)	23 (6.1%)	33~(8.8%)
max(byte, byte, byte)	22 (5.9%)	22 (5.9%)	25~(6.7%)
isDigits(String)	23 (6.1%)	23 (6.1%)	26~(6.9%)
isNumber(String)	51 (13.6%)	33 (8.8%)	76 (20.3%)

TABLE VI: The percentage for the correct test cases and the focal method coverage of A3Test, AthenaTest, and ChatUniTest on Defects4J dataset.

Projects	(Correct Test C	ases (%)	Focal Method Coverage (%)		
	A3Test	AthenaTest	${\bf Chat Uni Test}$	A3Test	AthenaTest	${\bf Chat Uni Test}$
Gson	14.09%	2.89%	23.30 %	40.90%	9.54%	55.91%
Cli	25.19%	11.07%	38.77 %	37.20%	29.46%	$\boldsymbol{70.34\%}$
Csv	25.73%	8.98%	44.26 %	37.80%	34.31%	76.94 %
Chart	31.30%	11.70%	39.02 %	34.40%	32.00%	79.56 %
Lang	49.50 %	23.35%	39.85%	58.30%	56.97%	84.05 %
Total	40.05%	16.21%	40.14%	46.80%	43.75%	79.67%

Answer to RQ 2

When comparing the performance of ChatUniTest to EvoSuite, ChatUniTest consistently outperforms EvoSuite in both branch and line coverage across 10 Java projects, achieving an average branch coverage of 90.61% and line coverage of 89.36%. In comparison to AthenaTest and A3Test, ChatUniTest excels in method line coverage for 15 of 17 methods in the NumberUtils class (Lang-1-f revision, Defects4J dataset), and outperforms both tools in correct test cases and focal method coverage. These results highlight ChatUniTest's robustness and superiority compared to state-of-the-art tools.

RQ3: What are the contributions of different components of ChatUniTest?

To investigate the individual contributions of the generation, rule-based repair, and ChatGPT-based repair components, we conducted an analysis of the test distribution after processing by each component. The results are presented in Figure 7. The figure indicates that the generation component produced fewer correct tests and

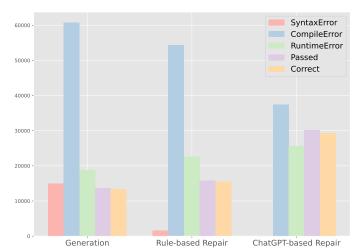


Fig. 7: Overall test distributions of different components

several syntactically incorrect tests. After processing by the rule-based repair component, syntactic errors were drastically reduced by 89.19%, compile errors were significantly decreased by 10.50%, and the number of correct tests increased by 15.54% from 13,391 to 15,472, primarily due to import repair. The ChatGPT-based repair compo-

nent, represented by the last set of bars, demonstrated its effectiveness as the most significant contributor, leading to a substantial reduction in compile error tests and a remarkable increase in the number of passed tests, by 90.63%, from 15,846 to 30,208. It is important to note that if the syntactic error cannot be fixed by the repair component, the attempt is terminated, thus will not be processed by ChatGPT-based component. To further in-

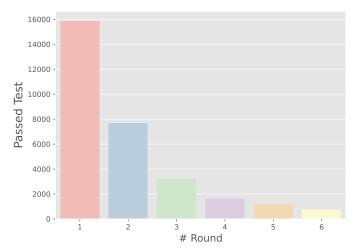


Fig. 8: Passed test distributions for each round

vestigate the effectiveness of ChatGPT-based repair, we presented the number of successfully passed tests for each round in Figure 8. Each round indicates the number of times ChatGPT was queried, meaning that a test had a chance to go through the Generation component once and ChatGPT-based repair five times. In Figure 8, we observe that nearly half of the total tests were fixed by ChatGPT-based repair. Additionally, we find that the number of repaired tests in rounds 2 through 6 was approximately half the quantity compared to the previous round. This suggests that the ChatGPT-based repair component plays a crucial role in enhancing test case generation, significantly improving the overall quality and effectiveness of ChatUniTest.

Answer to RQ 3

In the study of ChatUniTest's components, the generation component produced fewer correct tests and several syntactically incorrect ones. Rule-based repair drastically reduced syntactic errors by 89.19% and increased correct tests by 15.54%. However, ChatGPT-based repair emerged as the most significant contributor, increasing passed tests by 90.63% and substantially reducing compile errors. The analysis showed that ChatGPT-based repair played a crucial role in enhancing test case generation, significantly improving ChatUniTest's overall quality and effectiveness.

RQ4: How much does it cost to generate unit tests?

In this research question, we report the cost from several perspectives.

Figure 9 presents the total cost per method across various projects. We can observe that the total cost for generating unit tests varies across the projects, with the lowest being \$0.084 in the Ecommerce project and the highest being \$0.128 in the Flink project. This indicates that the complexity for test generation differ from across projects. Repair process accounts for the largest portion of the overall cost, at approximately 83%. Among these projects, Flink has the highest repair cost per method, approximately \$0.109, while Ecommerce has the lowest about \$0.073. In general, generation costs are significantly lower than repair costs for all projects.

Figure 10 demonstrates the correlation between prompt and completion token costs in the Generation component. A red regression line represents the mean trend. The green line signifies the sum of prompt and completion token costs equating to 4096 tokens, indicating that any point on this line has exceeded the maximum prompt token limit, resulting in a truncated response.

The vertical dotted line marks the maximum prompt token threshold set at 2700 tokens, with 99.95% of attempts remaining below this limit. The majority of the data points are situated within the range of 0 to 1000 tokens. The regression line's slope is approximately 0.077, and the correlation coefficient between prompt tokens and completion tokens is 0.09. This low correlation suggests that the completion token count remains relatively stable, irrespective of the prompt token count.

Figure 11 illustrates the correlation between prompt and completion token costs within the ChatGPT Repair component. The regression line's slope is 0.23, and the correlation coefficient is 0.44, signifying a moderate positive correlation between prompt tokens and completion tokens during the repair process. This relationship emerges because ChatGPT is tasked with returning a complete, corrected unit test after receiving the incorrect version.

To address this, a more efficient approach could involve requesting ChatGPT to provide instructions for modifying the original test without responding with the whole test. This could streamline the repair process, reduce token count, and improve overall efficiency, potentially optimizing the ChatGPT-based repair component and enhancing the test generation pipeline.

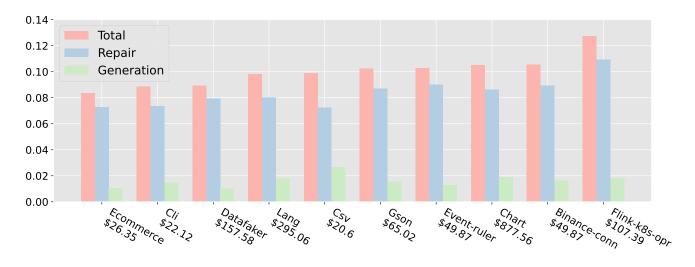


Fig. 9: Comparison of cost per method in total, repair, and generation across multiple projects

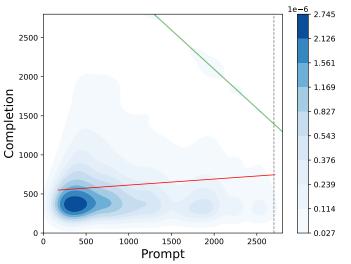
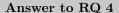


Fig. 10: Token cost relationship between prompt and completion in Generation component



The cost of generating unit tests varies across projects, with repair costs accounting for approximately 83% of the total cost. The correlation between prompt and completion token costs in the Generation component is low (0.09), suggesting completion token count remains relatively stable. In the Repair component, a moderate positive correlation (0.44) exists between prompt and completion tokens. A more efficient approach could involve requesting ChatGPT to provide instructions for modifying tests rather than returning the entire corrected test.

VI. CONCLUSION AND FUTURE WORK

In this study, we have introduced ChatUniTest, a ChatGPT-based automated unit test generation tool developed within the Generation-Validation-Repair frame-

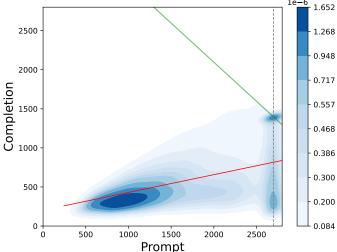


Fig. 11: Token cost relationship between prompt and completion in Repair component

work. ChatUniTest employs an adaptive focal context generation algorithm to produce informative prompts while adhering to the maximum prompt token limit, thus enabling ChatGPT to return untruncated responses. During the validation process, ChatUniTest utilizes a parser to ensure the unit test's syntactic correctness, a compiler to confirm its compile correctness, and a test executor to verify its runtime correctness. If an error occurs during validation, ChatUniTest first attempts to repair it using the Rule-based repair component. If this fails, ChatUniTest resorts to interact with ChatGPT for error correction. Our evaluation demonstrates that ChatUniTest outperforms EvoSuite in terms of branch and line coverage and surpasses AthenaTest and A3Test in focal method coverage.

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