

An Empirical Study of Using Large Language Models for Unit Test Generation

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Abstract

A code generation model generates code by taking a prompt from a code comment, existing code, or a combination of both. Although code generation models (*e.g.*, GitHub Copilot) are increasingly being adopted in practice, it is unclear whether they can successfully be used for unit test generation without fine-tuning. We investigated how well three generative models (Codex, GPT-3.5-Turbo, and StarCoder) can generate test cases to fill this gap. We used two benchmarks (HumanEval and Evosuite SF110) to investigate the context generation's effect in the unit test generation process. We evaluated the models based on compilation rates, test correctness, coverage, and test smells. We found that the Codex model achieved above 80% coverage for the HumanEval dataset, but no model had more than 2% coverage for the EvoSuite SF110 benchmark. The generated tests also suffered from test smells, such as Duplicated Asserts and Empty Tests.

Keywords:

test generation, unit testing, large language models, test smells

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1. Introduction

Automated code generation approaches generate code from *prompts* [1]. These prompts specify the developer’s intent and have varying level of granularity and structure. They may include sentences, code comments, code elements (*e.g.*, function signatures, expressions, *etc.*), or a combination of these. Thus, developers can write an initial code and/or comment and use these tools to generate the remaining code to speed up the software development process [2]. With the recent release of GitHub Copilot², these techniques are increasingly being adopted in industry [2]. GitHub Copilot relies on a transformer-based [3] Large Language Model (LLM) fine-tuned for code generation.

With the increasing popularity of LLMs prior works investigated the correctness of the generated code [4], their quality [5], security [6] and whether they can be used for API learning tasks [7], and code complexity prediction [8]. However, it is currently unclear the effectiveness of using prompt-based pre-trained code generation models to generate *unit tests*.

Unit testing is an important software maintenance activity because it helps developers identify and fix defects early; before they can propagate and cause more significant problems [9, 10, 11]. Moreover, unit tests help developers understand how the various code units in a software system fit together and work as a cohesive whole [12]. Given its importance, prior works developed automated test case generation techniques [13, 14].

To better understand the current capabilities of LLMs in generating unit tests, we conducted an empirical study using three LLMs (Codex [15], GPT-3.5-Turbo [16] and StarCoder [17]) to generate JUnit5 tests for classes in the HumanEval dataset’s Java version [18] and 47 open-source projects from the SF110 dataset [13]. In this empirical study, we answered two research questions. In the first question, we used the full class under test as a context for the LLMs to generate unit test cases. In the second research question, we examine how different context styles (*e.g.*, only using the method under test, the presence, and absence of JavaDoc *etc.*) can influence the generated tests. We examined the produced tests with respect to their compilation

²<https://github.com/features/copilot>

rates, correctness, code coverage, and test smells. To the best of our knowledge, concurrent works (CODAMOSA [19] and TestPilot [20]) are focused on the usefulness of LLM as a helper for search-based techniques and on weakly typed languages like Python and Javascript. Unlike these prior works, our work investigates whether LLMs can be used off-the-shelf to generate unit tests for a strongly-typed language like Java. Moreover, we examine these generated tests in terms of their correctness, quality, as well as the effectiveness of different context styles when generating tests.

The **contributions** of our work are:

- A systematic study of three LLMs for zero-shot unit test generation for 194 classes from 47 open-source projects in the SF110 dataset [21] and 160 classes from the HumanEval dataset [18].
- An investigation of the quality of the produced unit tests by studying the prevalence of test smells in the generated unit tests by different code generation models.
- A comparison of how different context styles affect the performance of LLMs in generating tests.
- A discussion about the implication of using code generation models for unit test generation in a Test Driven Development (TDD) environment.
- A replication package with all the scripts used to gather the data and spreadsheets compiling all the results³.

2. Background

This section defines core concepts needed for our work to be understood.

2.1. Unit Tests & Test Smells

The goal of **unit testing** is to validate that each program unit is working as intended and meets its requirements [22]. A **unit** refers to a piece of code that can be isolated and examined independently (*e.g.*, functions/methods, classes, *etc.*). In this work, **methods are our units under test**.

Just like production code, unit tests need to be not only *correct* but also satisfy other quality attributes, such as *maintainability* and *readability* [23].

³<https://doi.org/10.5281/zenodo.7875623>

Unit test smells (henceforth “test smells”) are indicators of potential problems, inefficiencies, or bad programming/design practices in a unit test suite [24, 25, 26, 27, 28]. They are often subtle and may not necessarily result in immediate failures or defects, but they can significantly impact the maintainability and effectiveness of the test suite over time [29]. There are many test smell types, ranging from tests that are too slow/fragile to tests that are too complex or too tightly coupled to implementing the code under test.

For example, the Java code in Listing 1 has a unit test for a method from the `LargestDivisor` class. It checks whether the Method Under Test (MUT) returns the largest divisor of a number. Although this test is correct, there is no explanation for the expected outputs passed to the assertions, which is a case of the **Magic Number Test** smell [29]. It also has multiple assertions in the same test method, an example of **Assertion Roulette** smell [27].

```

1 public class LargestDivisorTest {
2     @Test
3     void testLargestDivisor() {
4         assertEquals(5, LargestDivisor.largestDivisor(15));
5         assertEquals(1, LargestDivisor.largestDivisor(3));
6         assertEquals(1, LargestDivisor.largestDivisor(7));
7     }
8 }

```

LargestDivisorTest.java

Listing 1: Example of Unit Test and Unit Test Smell

2.2. Code Generation

Code generation techniques automatically generate source code from a given *prompt* [1], such as a text written in natural language, pseudocode, code comments *etc.* These techniques may also take into account the surrounding *context* when generating the code, such as file/variable names, other files in the software system, *etc.* The task of generating source code is also known as a *sequence-to-sequence (seq2seq) learning* problem [30]. Prior works tried to solve the seq2seq problem using Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) based neural network [30, 31]. Attention-based transformer architectures have recently been popular for solving this problem [3]. The transformer is a deep learning model built on an encoder-decoder architecture that leverages the self-attention mechanism to weigh the importance of each input data point [3]. Several well-known language models, like BERT (Bidirectional Encoder Representations from Transformers)

[32], T5 (Text-to-Text Transformer) [33] and GPT-3 (Generative Pre-trained Transformer) [34], are powered by the transformer architecture.

These large language models (LLMs) can be trained with source code to help with code-related tasks, *e.g.*, code completion [35, 36, 37], search [38], and summarization [39]. Examples of code-related LLMs include CodeBERT [38], CodeT5 [40], and CodeGen [41]. They take tokenized textual input and generate an output based on it. They also have input size limitations (*i.e.*, they accept/generate up to a certain amount of tokens). For example, the CodeGen [41] model can process up to 2,048 tokens.

3. Methodology

In this work, we answer two research questions.

RQ1 *How well can LLMs generate unit tests?*

We used GPT-3.5-Turbo, StarCoder, and Codex to generate unit tests for competitive programming assignments from the extended version of the HumanEval dataset [18] as well as 47 open-source projects from the EvoSuite SF110 benchmark dataset[13]. We measured the LLMs’ performance by computing the test’s branch/line coverage, correctness, and quality (in terms of test smells). We also compared the performance of these models with EvoSuite [13], an existing state-of-the-art approach.

RQ2 *How do code elements in a context influence the performance of LLMs in generating unit tests?*

When developers use LLMs to generate unit tests, they create a **prompt** (*e.g.*, “Write a unit test to verify that `login(req)` works correctly.”) and the unit under test becomes the **context** for that prompt. Since the unit under test (context) can include several *code elements*, we investigate how these different elements affect the generated tests in this question. To answer this question, we conducted a controlled experiment in which we created 3 different scenarios for the HumanEval [15, 18], and 4 scenarios for 47 open-source projects from the EvoSuite SF110 dataset[13]. Each scenario contains a different set of code elements. Then, we use Codex, GPT-3.5-Turbo, and StarCoder to generate JUnit tests for each scenario. We measured their

performance in terms of compilation rates, code coverage, the total number of correct unit tests, and the incidence of test smells.

3.1. Answering RQ1: LLM-based Unit Test Generation

To investigate whether existing models are capable of generating unit tests, we followed a three-step systematic process: ① we collected **160** Java classes from the **multilingual version of the HumanEval dataset** [18] and **194** Java classes from **47** projects in the **Evosuite SF110 benchmark dataset** [21, 42]; ② we generated JUnit5 tests using three LLMs; ③ we computed the compilation rates, correctness, number of smells, as well as the line/branch coverage for the generated tests and compared with Evosuite v1.2.0, which is a state-of-the-art unit test generation tool [13].

3.1.1. Data Collection

We retrieved Java classes from:

- The **multilingual HumanEval dataset** [18] contains **160 prompts** for Java and other programming languages crafted from the original Python-based HumanEval [15]. However, this multilingual version does not provide an implementation for each prompt (*i.e.*, a *canonical solution*). Thus, we wrote the solution for each problem and tested our implementation using the provided test cases. Our solution is encapsulated in a class as a **public static** method. Listing 2 shows a sample taken from this dataset⁴, where the prompt is in lines 1–12 and the solution is in lines 13–15.

```

1 import java.io.*;
2 import java.util.*;
3 import java.math.*;
4 class TruncateNumber {
5     /**
6      * Given a positive floating point number, it can be decomposed into an integer part
7      * (largest integer smaller than the given number) and decimals (leftover part always
8      * smaller than 1). Return the decimal part of the number.
9      * >>> truncateNumber(3.5)
10     * 0.5
11     */
12     public static Double truncateNumber(Double number) {
13         return Math.round( (number - Math.floor(number)) * 1000.0) / 1000.0;
14     }
15 }

```

Listing 2: Sample from the extended HumanEval [18]

⁴The code formatting is modified for a better presentation.

- The **SF110 dataset**, which is an Evosuite benchmark consisting of 111 open-source Java projects⁵ retrieved from SourceForge. This benchmark contains 23,886 classes, over 800,000 bytecode-level branches, and 6.6 million lines of code [43].

We use the multilingual HumanEval [18] because it has been widely used in prior works to evaluate LLMs trained on code [41, 44, 45, 5]. Similarly, we use the SF110 dataset because it is a popular benchmark for unit test generation techniques. Since its publication in 2014 [43], the paper has been cited around 200 times in the last week of March 2023 alone.

Class and Method Under Test Selection. Each class in the multilingual HumanEval [18] has one `public static` method and may also contain private “helper” methods to aid the solution implementation. In this study, all the public static methods are selected as methods under test (MUTs).

For the Evosuite benchmark, we first retrieved only the classes that are `public` and *not abstract*. We then discarded classes placed on a `src/test` folder, or that contains the keyword “Test” in its name (*i.e.*, test classes). Next, we identify testable methods by applying *inclusion* and *exclusion* criteria. The *exclusion* criteria are applied to the *non-static* methods that **(E1)** have a name starting with “get” and takes no parameters, *or* **(E2)** have a name starting with “is”, takes no parameter and returns a `boolean` value, *or* **(E3)** have a name starting with “set”, *or* **(E4)** override the ones from `java.lang.Object` (*i.e.*, `toString()`, `hashCode()`, *etc.*). The exclusion criteria **E1–E3** are meant to disregard “getter” and “setter” methods. The inclusion criteria are that the method has **(I1)** a `public` visibility, **(I2)** a `return` value, *and* **(I3)** a “good” JavaDoc. A *good* JavaDoc is one that **(i)** has a description *or* has a non-empty `@return` tag, and **(ii)** all the method’s parameters have an associated description with `@param` tag. After this step, we obtained a total of **30,916** methods under test (MUTs) from **2,951** classes.

Subsequently, we disregard projects based on the number of retrieved testable methods (MUTs). We kept projects with at least one testable method (*i.e.*, first quartile) and at most 31 testable methods (*i.e.*, third quartile), obtaining a total of **53** projects. This filtering aimed to remove projects with too *little*

⁵Though it is named SF110, upon further inspection, we noticed two projects have the same ID (82).

or too *many* MUTs, which would exceed the limit of the number of tokens that the models can generate. We then removed **6** of these projects in which we could not compile their source code, obtaining **47** projects and a total of **411** MUTs from **194** classes in the end.

3.1.2. Unit Test Generation

We used three LLMs to generate unit tests:

- **Codex** is a 12 billion parameters LLM [15] descendant of the GPT-3 model [34]. It powers the GitHub Copilot, which is available for writing source code in different programming languages. In this study, we used “code-davinci-002” (the most powerful codex model version of Codex).
- **GPT-3.5-turbo** is the model that powers the ChatGPT chatbot. It allows multi-turn conversation (*i.e.*, back-and-forth interactions) and can be instructed to generate code[16]. The GPT-3.5-Turbo API has three roles: *system*, *assistant*, and *user*. It takes instruction from the *user* role, and the *assistant* gives an answer. The *system* role is meant to help set the behavior of the *assistant* (*e.g.*, “You are a helpful assistant”).
- **StarCoder** is a 15.5 billion parameter open-source code generation model with 8,000 context length and has infilling capabilities. It is capable of generating code in more than 80 programming languages. In this work, we used the base model from the StarCoder code LLM series.

To generate tests using these LLMs, we performed a two-step process:

① **Context and Prompt Creation:** We created a *unit test prompt* (henceforth “prompt”), which instructs the LLM to generate **10** test cases for a specific method, and a *context*, which encompasses the whole code from the method’s declaring class as well as import statements to core elements from the JUnit5 API. Listing 3 illustrates the structure of these prompts and context, in which lines 1-11 (highlighted in blue) and lines 12–24 are part of the *context* and *prompt*, respectively. The context starts with a comment indicating the CUT’s file name followed by the CUT’s full code (*i.e.*, its package declaration, imports, fields, methods, *etc.*). Similarly, the prompt starts with a comment indicating the expected file name of the generated unit test. Since a class can have more than one testable method, we generated one unit test file for each testable method in a CUT and appended a suffix to avoid duplicated test file names. A suffix is a number that starts from zero.

After this code comment, the prompt includes the same package declaration and import statements from the CUT. It also has import statements to the `@Test` annotation and the `assert*` methods (e.g., `assertTrue(...)`) from JUnit5. Subsequently, the prompt contains test class' JavaDoc that specifies the MUT, and how many test cases to generate. The prompt ends with the test class declaration followed by a new line (`\n`), which will trigger the LLM to generate code to complete the test class declaration.

```

1 // L{className}.java
2 ${packageDeclaration}
3 ${importedPackages}
4 class ${className}{
5     /* ... code before the method under test ... */
6     public ${methodSignature}{
7         /* ... method implementation ... */
8     }
9     /* ... code after the method under test ... */
10 }
11
12 // L{className}L{suffix}Test.java
13 ${packageDeclaration}
14 ${importedPackages}
15 import org.junit.jupiter.api.Test;
16 import static org.junit.jupiter.api.Assertions.*;
17
18 /**
19  * Test class of {@link L{className}}. It contains L{numberTests} unit test cases for the
20  * {@link L{className}#L{methodSignature}} method.
21  */
22 class ${className}${suffix}Test {

```

Listing 3: Prompt template for RQ1

② **Test Generation:** Although all used LLMs can generate code, they have technical differences in terms of number of tokens they can handle. Thus, we took slightly different steps to generate tests with these LLMs.

- We leverage the OpenAI API to use the **Codex** model. This LLM can take up to 8,000 tokens as input and generate up to 4,000 tokens. Thus, we configured this model in two ways: one to generate up to 2,000 tokens and another to generate up to 4,000 tokens. We will call each of them *Codex (2K)* and *Codex (4K)*, respectively. For both cases, we set the model's `temperature` as zero in order to produce more deterministic and reproducible output motivated by previous studies [46, 47, 48]. The rest of its inference parameters are set to their default values.
- **GPT-3.5-Turbo** is also accessible via the OpenAI API. It can take up to 4,096 as input and generate up to 2,048 tokens. Hence, we asked this LLM

to generate up to 2,000 tokens and dedicated the rest (2,096) to be used as input. Its temperature is also set to zero and the other parameters are set to their defaults. Moreover, since it has three roles, we set the *system* role’s content to “*You are a coding assistant. You generate only source code.*” and the *user* role’s content to the context and prompt. Then, the *assistant* role is the one that provides the generated test code.

- **StarCoder** can be used with the HuggingFace library⁶. For this code LLM family, there are three models: StarCoderBase, StarCoder, and StarEncoder. We used the StarCoderBase model, which can generate more than 80 programming languages. It has an 8,000 tokens context window combining the input prompt tokens and the output tokens. We limit the output token to 2,000 tokens to align the experiment with the other two models. We also keep the same inference parameters as the Codex model.

3.1.3. Data Analysis and Evaluation

We compiled all the unit tests together with their respective production code and required libraries. As we compiled the code and obtained compilation errors, we observed that several of these errors were caused by simple *syntax* problems that could be automatically fixed through *heuristics*. Specifically, we noticed that LLMs may *(i)* generate an *extra* test class that is incomplete, *(ii)* include natural language explanations before and/or after the code, *(iii)* repeat the class under test and/or the prompt, *(iv)* change the package declaration or *(v)* remove the package declaration, *(vi)* generate integer constants higher than `Integer.MAX_VALUE`, *(vii)* generate incomplete unit tests after it reaches its token size limit. Thus, we developed **7** heuristics (**H1–H7**) to automatically fix these errors⁷:

- H1** It removes any code found *after* any of the following patterns: `"</code>"`, `"\n\n// {CUT_classname}"`, and `"\n```\n\n##"`.
- H2** It keeps code snippets within backticks (*i.e.*, ```` code ````) and removes any text before and after the backticks.
- H3** It removes the original prompt from the generated unit test.
- H4** It finds the package declaration in the unit test and renames it to the package of the CUT.

⁶<https://huggingface.co>

⁷Due to space constraints, we only provide a high-level description of these heuristics, but they are described in details on our replication package on Zenodo.

- H5** It adds the package declaration if it is missing.
- H6** It replaces large integer constants by `Integer.parseInt(n)`.
- H7** It fixes incomplete code by iteratively deleting lines (from bottom to top) and adding 1-2 curly brackets. At each iteration, it removes the last line and adds one curly bracket. If the syntax check fails, it adds two curly brackets and checks the syntax again. If it fails, it proceeds to the next iteration by removing the next line (bottom to top). The heuristic stops if the syntax check passes or it finds the class declaration (*i.e.*, “`class ABC`”), whichever condition occurs first.

Metrics. We ran each generated unit test with JaCoCo [49] to compute the *line coverage*, *branch coverage* and *test correctness* metrics:

- **Line Coverage** measures how many lines were executed by the unit test out of the total number of lines [50, 51], *i.e.*, $\frac{\text{Number of executed lines}}{\text{Total number of lines}} \times 100$.
- **Branch Coverage** is the most well-known and practiced metric in software testing [50] and measures how many branches are covered by a test. It is computed as: $\frac{\text{Number of visited branches}}{\text{Total number of branches}} \times 100$.
- **Test Correctness** measures how effectively an LLM generates correct input/output pairs. This study assumes that the code under test is implemented correctly. The reasoning behind this assumption is twofold: the HumanEval dataset contains common problems with well-known solutions (which we wrote and tested ourselves), and the SF110 projects are mature open-source projects. Given this assumption, a failing test case is considered to be *incorrect*. Thus, we compute the number of generated unit tests that did not fail.

We ran the tests using a timeout of **2** and **10** minutes for the HumanEval and the SF110 datasets, respectively, because we observed generated tests with infinite loops. Moreover, we analyzed the quality of the unit test from the perspective of the **test smells**. To this end, we used TsDETECT, a state-of-the-art tool that detects 20 test smell types [52, 28]. Due to space constraints, we provide a list of the test smells detectable by TsDETECT with their description and source in our replication package.

3.2. RQ2: Code Elements in a Context

To investigate how different code elements in a context influence the generated unit test, we first created *scenarios* for each of the 160 CUTs collected

in RQ1 from the multilingual HumanEval dataset [18] and the 194 CUTs from the 47 Java projects from the EvoSuite benchmark dataset [21, 42]. Next, we generated JUnit5 tests for each scenario. Lastly, we computed the same metrics as in RQ1 (Section 3.1.3).

3.2.1. Scenario Creation

We created *three* scenarios for the HumanEval dataset and *four* for the Evosuite Benchmark.

HumanEval Scenarios: Recall that each MUT in this dataset has a JavaDoc describing the method’s expected behavior and examples of input-output pairs (see Listing 1). Thus, the three scenarios are created as follows:

- S1** It does not contain any JavaDoc (*e.g.*, the JavaDoc from lines 5-11 within Listing 2 is removed from the CUT).
- S2** The JavaDoc does not include input/output examples, only the method’s behavior description (*e.g.*, Listing 2 will not have lines 9 and 10).
- S3** The MUT does not include its implementation, only its signature (*e.g.*, Listing 2 will not have lines 13 and 14).

The first two scenarios demonstrate the effect of changing the JavaDoc elements. Test-Driven Development (TDD) [53] inspires the last scenario approach, where test cases are written before the code implementation.

SF110 Scenarios: Unlike HumanEval, the CUTs from SF110 do not necessarily include input/output pairs. Thus, we generated scenarios slightly different than before:

- S1** It removes (i) any code within the CUT *before* and *after* the method under test as well as (ii) the MUT’s JavaDoc.
- S2** It is the same as S1, but *including* the JavaDoc for the method under test.
- S3** It is the same as S2, except that there is no method implementation for the MUT (only its signature).
- S4** It mimics S3, but it also includes all the fields and the signatures for the other methods/constructors in the CUT.

S1 and S2 demonstrate the effect of having or not having code documentation (JavaDoc). S3 aims to verify the usefulness of LLMs for TDD whereas S4 is used to understand how code elements are helpful for test generation.

We followed the same models and steps outlined in Section 3.1 to generate the unit tests. That is, we generated unit tests for each MUT and scenario combination. Then, we used JUnit5, JaCoCo, and TsDETECT to measure test coverage, correctness, and quality. Similar to RQ1, we also compared the results to Evosuite [13].

4. RQ1 Results: Unit Test Generation using LLMs

We analyze the generated unit tests according to four dimensions: (i) *compilation status*; (ii) *correctness*; (iii) *coverage*; and (iv) *quality*.

4.1. Compilation Status

Table 1 reports the percentage of generated unit tests that are compilable *before* and *after* applying the heuristic-based fixes described in Section 3.1.3. The number of unit tests and test methods for each model and dataset is shown in the last two columns of Table 1. As shown in this table, we obtained a total **2,536** test methods (*i.e.*, a method with an `@Test` annotation) scattered across **572** compilable Java test files for HumanEval. For SF110, we had **2,022** test methods and **600** compilable tests. For comparison, we also ran Evosuite [13] (with default configuration parameters) to generate unit tests for each of the CUTs. Moreover, in the case of HumanEval, we manually created a JUnit5 test for each input/output pair provided in each prompt (one test method per input/output pair).

Table 1: Compilation status of the generated unit tests

| | LLM | % Compilable | % Compilable (after fix) | #Test Methods | #Test Classes |
|-----------|----------------------|--------------|-----------------------------|------------------|------------------|
| HumanEval | GPT-3.5-Turbo | 43.1% | 81.3% | 1,117 | 130 |
| | StarCoder | 70.0% | 76.9% | 948 | 123 |
| | Codex (2K) | 37.5% | 100% | 697 | 160 |
| | Codex (4K) | 44.4% | 99.4% | 774 | 159 |
| | Evosuite | 100% | NA | 928 | 160 |
| | Manual | 100% | NA | 1,303 | 160 |
| SF110 | GPT-3.5-Turbo | 9.7% | 85.9% | 194 | 87 |
| | StarCoder | 12.7% | 69.8% | 1,663 | 368 |
| | Codex (2K) | 2.7% | 74.5% | 1,406 | 222 |
| | Codex (4K) | 3.4% | 83.5% | 1,039 | 152 |
| | Evosuite | 100% | NA | 12,362 | 1,618 |

HumanEval Results

We found that less than half of the unit tests generated by Codex (2K), Codex (4K), and GPT-3.5-Turbo are compilable for the classes in HumanEval. On one hand, only **37.5%**, **44.4%**, and **43.1%** of the unit tests generated by Codex (2K), Codex (4K), and GPT-3.5-Turbo are compilable, respectively. On the other hand, **70%** of StarCoder’s generated unit tests compiled.

Upon applying heuristic-based fixes, the compilation rates have increased an average of **41%**. The biggest increase was observed for the Codex (2K) model; its compilation rate increased from **37.5%** to **100%**. StarCoder was the LLM that the heuristics were the least able to improve; it only increased the compilation rate by **6.9%**.

SF110 Results

For the SF110 dataset, the compilation rates are lower than the ones observed for HumanEval. Between **2.7%** and **12.7%** of the generated unit tests for the SF110 dataset are compilable across all the studied LLMs. StarCoder was the LLM that generated the highest amount of compilable tests (**12.7%**), whereas Codex (2K) and Codex (4K) had the lowest compilation rate (**2.7%** and **3.4%**, respectively).

Similar to HumanEval, the heuristic-based fixes were able to increase the compilation rates by **81%**, on average. Codex was the model with the highest increase; the compilation rates increased from less than **5%** to over **99%**. StarCoder was the model that least benefited with our heuristics; its compilation rate increased by only **57.2%**.

Compilation error root causes

The unit tests that were not fixable through heuristics were those that contained *semantic* errors that failed the compilation. To observe the most common root causes of compilation errors, we collected all the compilation errors and clustered them using K-means [54]. We used the silhouette method [55] to find the number of clusters K ($K = 48$).

After inspecting these 48 clusters and making manual adjustments to clusters to fix imprecise clustering, we found that the top 3 compilation errors for HumanEval were caused by *unknown symbols* (*i.e.*, the compiler cannot find the symbol), *incompatible conversion from java.util.List<T> to java.util.List<X>*, and *incompatible conversion from int[] to*

`java.util.List<Integer>`. Unknown symbols accounted for more than **62%** of the compilation errors. Several of these unknown symbols were caused by invoking non-existent methods or instantiating non-existent classes. For example, StarCoder produced several test cases that invoked the method `of(int,int,int,...)` from `java.util.List`, which does not exist.

In the case of the SF110 dataset, the top 3 compilation errors were ***unknown symbols*** (*i.e.*, the compiler cannot find the symbol), ***class is abstract; cannot be instantiated***, and ***no suitable constructor found***. This differs from what we observed in HumanEval; one reoccurring problem was related to inheritance/polymorphism whereas the other is related to correctly instantiating objects.

4.2. Test Correctness

We executed each test that passed the compilation step after our automated fix using JUnit5. We considered a unit test to be ***correct*** if it had a success rate of **100%** (*i.e.*, *all* of its test methods passed) whereas a ***somewhat correct*** unit test is one that had *at least one* passing test method. As explained in Section 3.1.3, the reasoning behind these metrics is that the HumanEval has a canonical solution which is the *correct* implementation for the problem. Thus, a correct test must not fail (or else the input/output generated does not match the benchmark’s problem). Similarly, as the SF110 benchmark is a popular benchmark for automatic test generation containing mature open-source projects, they have a higher probability that they are functionally correct. Both metrics are reported in Table 2.

HumanEval Results

StarCoder generated the highest amount of correct unit tests ($\approx 81\%$). It is worth mentioning that although GPT-3.5-Turbo only produced **52%** correct unit tests, it was the model that generated the highest amount of tests that have at *at least one* passing test method (**92.3%**). We also found that increasing Codex’s token size did not yield higher correctness rates.

Between **52%** to **81%** of generated tests were correct whereas **81%-92%** of the tests had *at least one* passing test case. From these results, we can infer that although all the models could not produce correct tests, they can still be useful in generating at least a few viable input/output pairs.

Table 2: Percentage of correct tests for HumanEval (HE) and SF110

| | | GPT-3.5-Turbo | StarCoder | Codex (2K) | Codex (4K) |
|-------|--------------------|---------------|-----------|------------|------------|
| HE | % Correct | 52.3% | 81.3% | 77.5% | 76.7% |
| | % Somewhat Correct | 92.3% | 81.3% | 87.5% | 87.4% |
| SF110 | % Correct | 6.9% | 51.9% | 46.5% | 41.1% |
| | % Somewhat Correct | 16.1% | 58.6% | 62.7% | 53.7% |

SF110 Results

The best performing model for the SF110 dataset was StarCoder, which produced **51.9%** correct tests. Codex (2K) was the best performing LLM for generating unit tests that have *at least one* passing test case.

For this dataset, the correctness rates achieved by the LLMs are rather low. Less than **52%** of the produced tests are correct for all models. Even when considering the unit tests that produced at least one passing test case (*somewhat correct*), only up to **63%** fulfill this criterion.

4.3. Test Coverage

We measured the generated unit tests’ line and branch coverage and compared them with the coverage for the tests generated by Evosuite [13]. For HumanEval, we also compared the coverage of the manually created tests.

HumanEval Results

Table 3 shows the line and branch coverage for the HumanEval dataset, computed considering all the Java classes in the dataset. The results show that the LLMs achieved line coverage ranging from **67%** to **87.7%** and branch coverage ranging from **69.3%** to **92.8%**. Codex (4K) exhibited the highest line and branch coverage of **87.7%** and **92.8%**, respectively. However, the coverage of the unit tests generated by LLMs are below the coverage reported by the manual tests and those generated by Evosuite. In fact, Evosuite, which relies on an evolutionary algorithm to generate JUnit tests, has a higher line and branch coverage than the manually written tests.

SF110 Results

The test coverage for SF110 is drastically worse when compared to HumanEval. In fact, the branch and line coverages were less than **2%** for all models. Among the LLMs, Codex (2K) was the best performing one in terms of line coverage (**1.9%**), whereas GPT-3.5-Turbo had the highest branch

Table 3: Line and branch coverage

| | Metric | GPT-3.5-Turbo | StarCoder | Codex-2K | Codex-4K | Evosuite | Manual |
|-----------|-----------------|---------------|-----------|----------|----------|----------|--------|
| HumanEval | Line Coverage | 69.1% | 67.0% | 87.4% | 87.7% | 96.1% | 88.5% |
| | Branch Coverage | 76.5% | 69.3% | 92.1% | 92.8% | 94.3% | 93.0% |
| | | | | | | | |
| SF110 | Line Coverage | 1.3% | 1.1% | 1.9% | 1.2% | 27.5% | – |
| | Branch Coverage | 1.6% | 0.5% | 1.1% | 0.7% | 20.2% | – |
| | | | | | | | |

coverage (**1.6%**). Yet, these coverages are $\approx 11\text{-}19\times$ lower than the coverage achieved by Evosuite’s tests.

4.4. Test Smells

We used TSDETECT [52] to find smells on the unit tests generated by the LLMs as well as the ones created manually and generated by Evosuite.

HumanEval Results

Table 4 shows the distribution of test smells in different LLMs⁸. The LLMs produced the following smells: Assertion Roulette (AR) [27], Conditional Logic Test (CLT) [29], Empty Test (EM) [28], Exception Handling (EH) [28], Eager Test (EA) [27], Lazy Test (LT) [27], Duplicate Assert (DA) [28], Unknown Test (UT) [28], , and Magic Number Test (MNT) [29]. We found that Magic Number Test (MNT) and Lazy Test (LT) are the two most reoccurring test smell types across *all* the approaches, *i.e.*, in the unit tests generated by the LLMs and Evosuite as well as the ones created manually. The **MNT** smell occurs when the unit test hard-codes a value in an assertion without a comment explaining it, whereas the **LT** smell arises when multiple test methods invoke the same production code.

Whereas Codex, StarCoder, and GPT-3.5-Turbo did not produce unit tests with the Exception of Handling (EH) smell, this smell type was frequent in all test cases manually created and those generated by Evosuite. We also found that **Assertion Roulette (AR)** is a common smell produced by LLMs (frequency between **23.8%** – **61.3%**) and that also occurred in Evosuite in

⁸We hide *Default Test*, *General Fixture*, *Mystery Guest*, *Verbose Test*, *Resource Optimism*, *Dependent Test*, and other test smell types supported by TSDETECT because they did not occur in any of the listed approaches

Table 4: Test smells distribution for the HumanEval dataset (RQ1).

| Test Smell | Codex (2K) | Codex (4K) | StarCoder | GPT-3.5-Turbo | Evosuite | Manual |
|------------|------------|------------|-----------|---------------|----------|--------|
| AR | 61.3% | 59.7% | 51.3% | 23.8% | 15.0% | 0.0% |
| CLT | 0.0% | 0.0% | 0.0% | 1.5% | 0.0% | 0.0% |
| EM | 1.9% | 1.3% | 3.8% | 0.8% | 0.0% | 0.0% |
| EH | 0.0% | 0.0% | 0.0% | 0.0% | 100.0% | 100.0% |
| EA | 60.6% | 59.1% | 48.8% | 23.8% | 16.3% | 0.0% |
| LT | 39.4% | 41.5% | 51.3% | 86.2% | 99.4% | 100.0% |
| DA | 15.6% | 14.5% | 10.6% | 3.1% | 0.6% | 0.0% |
| UT | 10.0% | 5.7% | 6.3% | 0.8% | 0.0% | 0.0% |
| MNT | 100.0% | 100.0% | 100% | 100.0% | 100.0% | 100.0% |

15% of its generated tests. This smell occurs when the same test method invokes an `assert` statement to check for different input/output pairs and does not include an error message for each of these asserts. Similarly, the LLMs and Evosuite also produced unit tests with the **Eager Test** smell (EA), in which a single test method invokes different methods from the production class, as well as the **Duplicate Assert** smell (DA) (caused by multiple assertions for the same input/output pair).

SF110 Results

The smells detected for the SF110 tests are listed in Table 5. Similar to HumanEval, **Magic Number Test** (MNT), **Assertion Roulette** (AR), and **Eager Tests** (EA) are frequently occurring smells in the unit tests generated by the LLMs and Evosuite. The LLMs generated other types of smells that were not observed for the HumanEval dataset, namely **Constructor Initialization** (CI) [28], **Mystery Guest** (MG) [27], **Redundant Print** (RP) [28], **Redundant Assertion** (RA) [28], **Sensitive Equality** (SE) [27], **Ignored Test** (IT) [28], and **Resource Optimism** (RO) [28].

While LLMs produced tests that had **Empty Tests** (EM), **Redundant Print** (RP), **Redundant Assertion** (RA), and **Constructor Initialization** (CI) smells, Evosuite did not generate any unit test with these smell types. We also observed that StarCoder generated (proportionally) more samples than the other models (**96.7%** of its generated tests had at least one test smell).

5. RQ2 Results: Code Elements in a Context

Similar to RQ1, we investigated how code elements in a context influence the generated unit tests with respect to their *compilation status*, *correctness*, *coverage*, and *quality*.

Table 5: Test smells distribution for the SF110 dataset (RQ1).

| Test Smell | GPT-3.5-Turbo | StarCoder | Codex (2K) | Codex (4K) | Evosuite |
|------------|---------------|-----------|------------|------------|----------|
| AR | 4.6% | 35.1% | 14.4% | 17.1% | 35.0% |
| CLT | 2.3% | 2.4% | 0.5% | 1.3% | 0.0% |
| CI | 0.0% | 4.9% | 0.0% | 0.7% | 0.1% |
| EM | 0.0% | 3.8% | 7.2% | 1.3% | 0.0% |
| EH | 2.3% | 18.2% | 20.7% | 19.1% | 91.2% |
| MG | 0.0% | 3.5% | 2.7% | 3.3% | 3.0% |
| RP | 0.0% | 10.6% | 4.5% | 5.9% | 0.0% |
| RA | 0.0% | 0.3% | 0.9% | 0.7% | 0.0% |
| SE | 0.0% | 1.9% | 0.9% | 1.3% | 13.7% |
| EA | 12.6% | 39.7% | 28.4% | 31.6% | 39.6% |
| LT | 21.8% | 33.4% | 60.8% | 60.5% | 46.4% |
| DA | 1.1% | 11.7% | 1.4% | 2.0% | 1.5% |
| UT | 0.0% | 21.2% | 21.2% | 10.5% | 22.9% |
| IT | 0.0% | 0.3% | 0.0% | 0.0% | 0.0% |
| RO | 0.0% | 4.6% | 2.7% | 3.9% | 2.7% |
| MNT | 21.8% | 95.4% | 93.2% | 96.1% | 91.2% |

5.1. Compilation Status

Fig. 1 shows the compilation rates for the HumanEval and SF110 datasets across the different scenarios and LLMs.

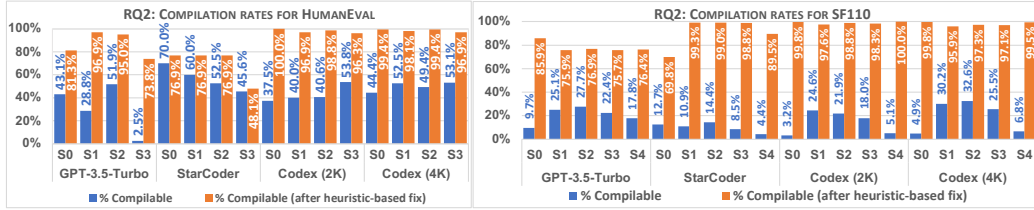


Figure 1: Compilation rates for HumanEval and SF110 across different scenarios

HumanEval Results

Scenario 3 (**S3**) increased the original (**S0**) compilation rates for Codex (2K and 4K) from 37.5%, and 44.4% to **53.8%** and **53.1%**, respectively. Although scenario 3 increased the original compilation rates (blue bars in Fig. 1) these tests have similar heuristic-based fix rates. In the case of StarCoder, the original prompt (**S0**) was the best in generating compilable code.

GPT-3.5-Turbo, on the other hand, experienced a sharp decrease from 43.1% to 2.5% for S3. Upon further inspection, we found that scenario 3 triggered GPT-3.5-Turbo 3.5 to include the original class under test in its entirety followed by the unit test. This resulted in two package declarations on the

produced output; one placed in the very first line (corresponding to the CUT’s package) and the other placed after the CUT for the unit test’s package. These duplicated package declarations lead to compilation errors. These issues were later fixed by applying the heuristic **H3**. For the GPT-3.5-Turbo model, the best performing context scenario was **S2**, in which the prompt does not include sample input/output pairs.

SF110 Results

S2 increased the original (**S0**) compilation rates for GPT-3.5-Turbo, StarCoder, and Codex (4K), as shown in Fig. 1. However, scenario 1 (**S1**) was the best performer for Codex (2K), while scenario 2 (**S2**) was the second-best performer. What these results show is that it is beneficial to include a *minimal* context which contains only the MUT’s implementation when generating test cases. The benefit seems twofold: (1) it can increase the compilation rate of the generated code snippets, and (2) it consumes less input tokens, as other methods from the class under test are removed.

5.2. Test Correctness

Fig. 2 shows the percentage of unit tests generated by the LLMs that are *correct* for the HumanEval and SF110 datasets. The scenarios with the highest performance for that LLM are highlighted in green.

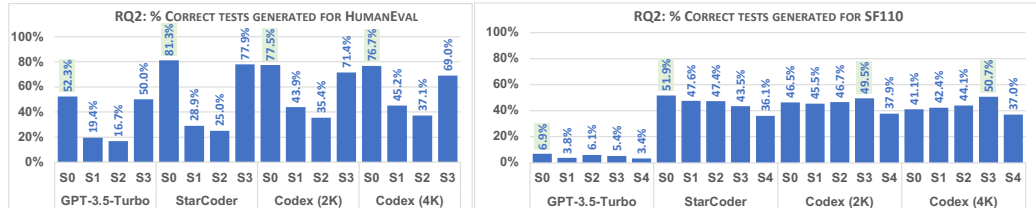


Figure 2: Correctness rates across different datasets, scenarios, and LLMs

HumanEval Results

We observe that the original context (**S0**) is the one that lead to the highest amount of correct tests for the HumanEval dataset. Among all scenarios, scenario 3 (**S3**) had a *similar* correctness rate compared to the original prompt used in RQ1 for GPT-3.5-Turbo and Codex (2K, 4K). It is important to highlight that whereas GPT-3.5-Turbo only had 73.8% compilable tests in scenario3 (compared to 81.3% tests from the original prompt) it still had a

similar correctness rate. Yet, the original prompt is the one that has the highest correctness rates.

Recall that scenario 3 (**S3**) is the one in which the implementation of the method under test is not included in the prompt. These results show that LLMs can still generate unit tests even if the implementation is not provided. Such a scenario can be useful in TDD; where developers write tests *before* the production code.

• **Effects on including input/output examples on the prompt.** The HumanEval dataset has input/output examples in its problem description (see Listing 2). Thus, for this dataset, we also investigated to what extent LLMs are able to generate unique input/output pairs that are not included in the original problem description and how these related to the test correctness rates observed. We manually inspected each generated test to compute the *total number of unique input/output pairs* generated. For each unique input/output pair, we compared with the ones provided in the problem’s description in order to compute the *total number of input-output pairs that are from the problem description* and the *total number of input-output pairs that are not in the problem description*.

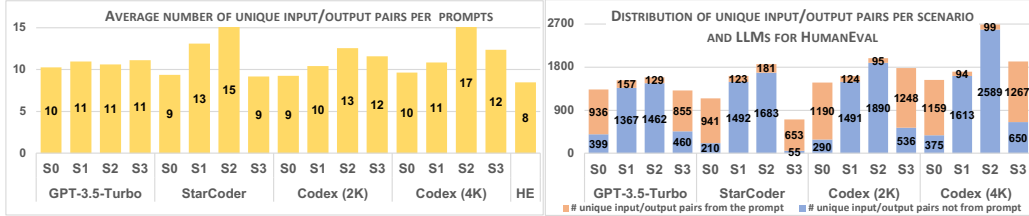


Figure 3: *Left*: Average number of unique input/outputs per prompt for each LLM and the original dataset (HumanEval - HE). *Right*: Total number of unique input/outputs that are and are not from the problem’s description.

Fig. 3 (*left*) shows the average number of unique input/output pairs for each LLM and scenario combination compared to the problem description in the HumanEval dataset. We can observe that each problem in HumanEval dataset provides an average of **8** input/output pair examples, whereas the LLMs provide more than that, as the prompts explicitly request 10 test cases for each problem description. We can also observe that the scenarios **S1** and

S2, which do not include input-output pairs in the prompt, has a *higher* average of number of unique input output pairs.

Fig. 3 (right) shows how many of the generated input/output pairs by the LLMs are from the problem’s description and how many are not. We found that the scenarios **S1** and **S2** generated *more* input-output pairs that are not from the original description, whereas the scenarios **S0** and **S3** are repeating the test cases from the prompt. That is, the models are behaving like “parrots” [56] by using the same input/output in the prompt and just formatting it as a test case without generating new examples. When contrasting with the correctness rates observed in Fig. 2 we can see that scenarios **S1** and **S2** were consistently lower for all LLMs. These results show that although scenarios **S1** and **S2** generated *more* input-output examples, those were not necessarily correct. The prompts that included examples of input-outputs had higher correctness rates.

SF110 Results

While the original prompt (**S0**) achieved the highest correctness rate for GPT-3.5-Turbo (6.9%) and StarCoder (51.9%), the other LLMs observed a correctness increase when using the context from scenario 3 (**S3**). Codex (4K) experienced the highest increase (from 37.9% to 50.7%) for S3. This scenario (**S3**) has a context which only includes the MUT’s Javadoc and signature and removes other methods from the class where the MUT is declared.

5.3. Test Coverage

Fig. 4 shows the *line* and *branch* coverage for each scenario and LLMs.

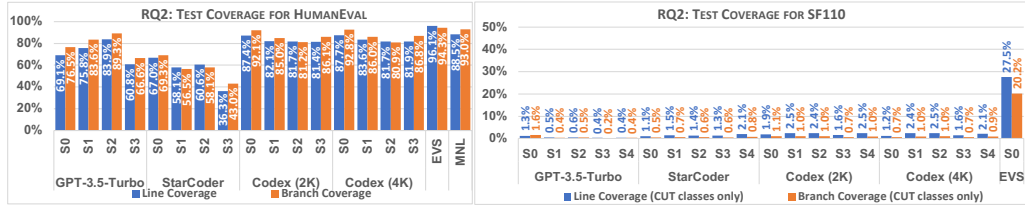


Figure 4: Line and Branch Coverage across different datasets, scenarios, and LLMs (EVS = Evosuite; MNL = Manual).

HumanEval Results

In the case of Codex, scenario 1 is the one that had the highest line coverage among the different scenarios in these models. GPT-3.5-Turbo and StarCoder, on the other hand, had scenario 2 as the one with the highest line coverage.

With respect to *branch* coverage, we found that scenario 3 was the best performing one for Codex, and scenario 2 is the best one for GPT-3.5-Turbo and StarCoder. None of the scenarios for Codex (2K and 4K) and StarCoder outperformed the line/branch coverage of the original prompts nor the coverage achieved by the manual and Evosuite’s tests.

SF110 Results

Among all scenarios, scenario 1 (**S1**) and scenario 2 (**S2**) had a slightly higher line coverage when compared to the original prompt used in RQ1 for Codex (2K) and Codex (4K), respectively. For StarCoder the scenario 4 had a higher line coverage than the original one. The original context of GPT-3.5-Turbo, on the other hand, had the highest observed line coverage.

In the case of branch coverage, scenario 1 (**S1**) had slightly higher coverage for Codex (4K), whereas scenario 4 (**S4**) was the best one for StarCoder. However, these increases are still much lower than Evosuite’s test coverage, which achieved $\approx 27\%$ line and branch coverage.

5.4. Test Smells

HumanEval Results

Table 6 shows the distribution of smells for different scenarios and LLMs. The cells highlighted in **green** are those in which the percentage is lower than the original context, whereas those highlighted in **red** have a higher percentage than the original context. In terms of smell types, all scenarios have the same smell types that occurred in the original prompts (see Table 4). Moreover, we also observe that, overall, the scenarios tended to decrease the incidence of generated smells. When comparing each scenario to one another, there is no clear outperformer across all the LLMs. Yet, Scenario 3 for GPT-3.5-Turbo had higher percentages than the original context, on average. Although the average increases are not significant (0.6% and 0.2% for these LLMs, respectively).

Table 6: Test smells distribution for the HumanEval dataset (RQ2).

| | GPT-3.5-Turbo | | | StarCoder | | | Codex (2K) | | | Codex (4K) | | |
|-----|---------------|-------|-------|-----------|-------|-------|------------|-------|-------|------------|-------|-------|
| | S1 | S2 | S3 | S1 | S2 | S3 | S1 | S2 | S3 | S1 | S2 | S3 |
| AR | 7.1% | 11.8% | 30.5% | 36.9% | 36.3% | 48.1% | 16.8% | 38.6% | 61.0% | 16.6% | 40.3% | 63.2% |
| CLT | 6.5% | 3.3% | 0.8% | 0.0% | 0.6% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% |
| EM | 0.0% | 0.7% | 3.4% | 1.9% | 8.1% | 3.8% | 4.5% | 3.2% | 1.9% | 1.3% | 1.3% | 1.9% |
| EA | 7.1% | 10.5% | 26.3% | 28.8% | 30.0% | 48.1% | 15.5% | 37.3% | 56.5% | 15.3% | 38.4% | 58.1% |
| LT | 85.2% | 92.8% | 82.2% | 61.9% | 63.8% | 53.1% | 84.5% | 60.8% | 44.2% | 84.7% | 60.4% | 42.6% |
| DA | 1.3% | 0.0% | 1.7% | 8.1% | 11.3% | 11.3% | 0.6% | 8.2% | 11.0% | 1.9% | 6.9% | 11.6% |
| UT | 0.0% | 0.7% | 3.4% | 11.3% | 13.8% | 6.3% | 13.5% | 16.5% | 2.6% | 5.1% | 8.2% | 2.6% |
| MNT | 89.7% | 98.7% | 100% | 99.4% | 99.4% | 100% | 100% | 100% | 100% | 100% | 100% | 100% |

SF110 Results

As shown Table 7, there is not any scenario that consistently outperforms the other. However, we can observe that scenario 2 for GPT-3.5-Turbo produces more test smells than the other scenarios, as we can see from the cells highlighted in red.

Table 7: Test smells distribution for the SF110 dataset (RQ2).

| | Codex (2K) | | | | Codex (4K) | | | | StarCoder | | | | GPT-3.5-Turbo | | | |
|-----|------------|-------|-------|-------|------------|-------|-------|-------|-----------|-------|-------|-------|---------------|-------|-------|-------|
| | S1 | S2 | S3 | S4 | S1 | S2 | S3 | S4 | S1 | S2 | S3 | S4 | S1 | S2 | S3 | S4 |
| AR | 17.3% | 12.8% | 12.4% | 7.8% | 17.5% | 13.5% | 13.6% | 8.3% | 23.0% | 23.5% | 21.4% | 27.1% | 6.6% | 7.8% | 4.4% | 12.1% |
| CLT | 0.0% | 0.5% | 0.0% | 0.7% | 0.0% | 0.0% | 0.0% | 0.8% | 1.4% | 1.6% | 1.4% | 1.1% | 0.5% | 1.7% | 1.1% | 3.5% |
| CI | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.2% | 0.0% | 0.0% | 1.1% | 0.0% | 0.0% | 0.0% | 0.0% |
| EM | 8.2% | 5.1% | 24.8% | 5.9% | 7.7% | 5.0% | 21.6% | 5.4% | 1.4% | 1.6% | 2.9% | 2.9% | 0.0% | 0.0% | 1.1% | 2.1% |
| EH | 14.3% | 19.5% | 15.3% | 24.5% | 15.5% | 18.5% | 14.1% | 25.7% | 17.2% | 22.5% | 25.3% | 21.5% | 2.2% | 3.3% | 2.7% | 5.0% |
| MG | 2.0% | 1.5% | 1.0% | 2.6% | 1.0% | 1.5% | 1.5% | 2.5% | 2.2% | 2.7% | 2.4% | 2.7% | 1.6% | 1.1% | 1.1% | 3.5% |
| RP | 2.0% | 2.1% | 4.0% | 3.0% | 1.5% | 2.5% | 4.0% | 2.9% | 6.8% | 16.5% | 14.1% | 10.7% | 0.0% | 0.0% | 0.0% | 0.7% |
| RA | 1.0% | 0.5% | 1.0% | 1.5% | 0.5% | 0.5% | 1.0% | 1.2% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.5% | 0.7% |
| SE | 1.0% | 0.0% | 1.5% | 1.5% | 1.0% | 0.5% | 1.0% | 1.2% | 0.6% | 0.2% | 0.4% | 0.9% | 0.5% | 0.6% | 1.1% | 2.1% |
| EA | 16.8% | 14.4% | 11.4% | 20.8% | 17.0% | 13.0% | 11.6% | 25.3% | 24.6% | 28.7% | 20.8% | 35.1% | 7.7% | 8.3% | 6.6% | 15.6% |
| LT | 31.6% | 44.1% | 32.7% | 55.8% | 33.0% | 46.0% | 35.2% | 57.7% | 30.1% | 26.0% | 27.1% | 32.4% | 14.2% | 16.7% | 13.7% | 22.0% |
| DA | 6.1% | 1.5% | 1.5% | 1.9% | 5.2% | 2.5% | 2.0% | 2.5% | 6.4% | 4.5% | 5.1% | 7.2% | 2.2% | 1.7% | 0.5% | 2.8% |
| UT | 14.8% | 12.3% | 30.7% | 17.8% | 12.9% | 10.5% | 24.1% | 16.6% | 17.8% | 16.7% | 19.4% | 20.6% | 0.0% | 0.0% | 1.6% | 2.1% |
| RO | 1.5% | 1.5% | 2.0% | 2.2% | 1.0% | 1.5% | 2.5% | 2.9% | 3.6% | 3.3% | 3.7% | 4.0% | 1.6% | 1.1% | 1.1% | 2.8% |
| MNT | 98.5% | 98.5% | 98.0% | 91.8% | 97.9% | 97.5% | 98.5% | 95.0% | 91.2% | 96.9% | 99.0% | 96.4% | 18.6% | 21.1% | 18.0% | 29.1% |

6. Results Summary and Implications

In this section, we summarize the findings and discuss their implications.

– **LLMs vs. Evosuite:** Across all the studied dimensions, LLMs performed worse than Evosuite. One reason is that LLMs do not always produce compilable unit tests, as we showed in Table 1. For example, while Evosuite produced one unit test for each of the 160 classes under test, GPT-3.5-Turbo

only produced **130** compilable (*i.e.*, executable) unit tests. Another reason is that LLMs do not seem to pay attention to the current MUT’s implementation. A piece of evidence for this is that scenario 3 (which does not include the MUT’s implementation) has better compilation rates than the rest. However, we also observed that ChatGPT generated test cases for “stress-testing”, such as using `Integer.MAX_VALUE` and similar inputs in order to test for the MUT’s behavior in the face of exceptionally large inputs.

- **Codex and StarCoder perform better than GPT-3.5-Turbo.** This can be explained by the fact that Codex and StarCoder are LLMs fine-tuned for code-related tasks in contrast to GPT-3.5-Turbo, which is tailored to dialogues (natural language).
- **LLMs often “hallucinate” inexistent types, methods, *etc.*** For both datasets, the most common compilation error was due to missing symbols. For instance, Codex generated inputs whose type were `Tuple`, `Pair`, `Triple`, `Quad`, and `Quint`, which are non-existent in Java’s default classpath.
- **Synergy between LLMs and TDD.** Although LLMs were not capable of achieving coverages or compilation rates comparable to Evosuite, the LLMs can still be useful as a starting point for TDD. As we showed in our RQ2, LLMs can generate tests based on the MUT’s JavaDoc. However, given the low correctness rates of LLMs, developers would still need to adjust the generated tests manually.

Given these findings, we observe a need for future research to focus on helping LLMs in reason over data types and path feasibility, as well as exploring the combination of SBST and LLMs for TDD. Furthermore, a recent study [2] surveyed 2,000 developers and analyzed anonymous user data, showing that GitHub Copilot makes developers more productive because the generated code can automate repetitive tasks. Thus, our findings provide some initial evidence that *practitioners* following a TDD approach could benefit from LLM-generated tests as a means to speed up their testing. Although further user studies would be needed to verify this hypothesis.

6.1. Threats to Validity

Creating canonical solutions for the Java samples in the HumanEval dataset [18] introduced an internal validity threat. To mitigate it, we extensively vetted our solution with a test set provided by the dataset creator; they passed the test cases without any problem. Another validity threat relates to the use

of SF110 benchmark [13], JaCoCo [49] for calculating coverage results and TsDetect [52] for finding test smells. In this case, our analyses depend on the representativeness of the SF110 dataset (construct validity threat) and the accuracy of these tools. However, the SF110 dataset is commonly used to benchmark automated test generation tools [13, 57, 58] and the used tools are well-known among researchers and practitioners [59, 60].

7. Related Work

Previous works have focused on creating source code that can do a specific task automatically (code generation). The deductive synthesis approach [61, 62], in which the task specification is transformed into constraints, and the program is extracted after demonstrating the satisfaction of the constraints, is one of the foundations of program synthesis [63]. Recurrent networks were used by Yin *et al.* [64] to map text to abstract syntax trees, which were subsequently coded using attention. A variety of large language learning models have been made public to generate code (e.g., CodeBert [38], CodeGen [41] and CodeT5 [40]) after being refined on enormous code datasets. Later, GitHub Copilot developed an improved auto-complete mechanism using the upgraded version of Codex [15], which can help to solve fundamental algorithmic problems [4]. Recent works [65, 66, 67] focus on optimizing the process to create, fine-tune, and infer the Large Language Models-based code generation techniques. Using large language models for software test generation is not that common. However, they can be used for downstream tasks, for example, flaky test prediction [68]. However, recent work uses GPT-3 [34] for software graphical interface testing [69]. Our work focuses not on code generation but on how a publicly available code generation tool can be used for specialized tasks like unit test generation without fine-tuning (*i.e.*, zero-shot test generation).

Shamshiri *et al.* [11] proposed a search-based approach that automatically generates tests that can reveal functionality changes, given two program versions. On the other hand, Tufano *et al.* [70] proposed an approach that aims to generate unit test cases by learning from real-world focal methods and developer-written test cases. Pacheco *et al.* [71] presented a technique that improves random test generation by incorporating feedback obtained from executing test inputs as they are created for generating unit tests. Pecorelli *et al.* [72] conducted an empirical study on software testing for Android

applications about finding effectiveness, design, and bugs in the production code. In our work, we focus on zero-shot unit test generation using different contexts in order to measure the LLM’s ability to generate compilable, correct and smell-free tests.

Schäfer *et al.* [20] used Codex [15] to automatically generate unit tests using an adaptive approach. They used 25 npm packages to evaluate their tool, TESTPILOT. However, they evaluated their model only on statement coverage. They did not provide insight into the quality of the generated test cases and the choice of using a specific prompt structure. Lemieux *et al.* [19] combined the Search-based software testing (SBST) technique with the LLM approach. It explored whether Codex can be used to help SBST’s exploration. Nashid *et al.* [73] aimed to devise an effective prompt to help large language models with different code-related tasks, *i.e.*, program repair and test assertion generation. Their approach provided examples of the same task and asked the LLM to generate code for similar tasks. Bareiß *et al.* [74] performed a systematic study to evaluate how a pre-trained language model of code, Codex, works with code mutation, test oracle generation from natural language documentation, and test case generation using few-shot prompting like Nashid *et al.* [73]. However, the benchmark has only 32 classes, so the findings may not be generalized. This work provides direction toward using examples of usage or similar tasks as a context. However, in a real case, there may not be any example of using the method and class that can be used in the prompt, and creating an example of a similar task needs human involvement. Our work focused on different contexts taken from the code base. We evaluated the quality of the generated unit tests not only on coverage and correctness but also based on the presence of test smells.

8. Conclusion

We investigated the capability of three code generation models for unit test generation. We conducted experiments with different contexts in the prompt and compared the result based on compilation rate, test correctness, coverage, and test smells. These models have a close performance with the state-of-the-art test generation tool for the HumanEval dataset, but their performance is poor for open-source projects from Evosuite based on coverage. Though our developed heuristics can improve the compilation rate, several generated tests were not compilable. Moreover, they heavily suffer

from test smells like Assertion Roulette and Magic Number Test. In future work, we will explore how to enhance LLMs to understand language semantics better in order to increase test correctness and compilation rates.

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