Generative AI to Generate Test Data Generators

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1. Introduction

Software tests require data that is realistic, but not real. For example, banking applications cannot be tested with actual customer names and addresses. In these situations, developers rely on fake data generators, also known as fakers, to generate test data to be used in automated tests. Fakers exist in all programming languages. For example, the faker gem and java-faker are popular faking libraries for the Ruby and Java languages. Faking libraries usually include generators for names, phone numbers, and addresses. The development of test data generators is challenging, as they must consider several constraints. For example, name generators must capture the cultural sphere into which the system under test is being deployed. In many Spanish-speaking countries, a family name generator must output two names separated by a space. Another constraint relates to humor, as fakers have been proven to be a strong vector of healthy humor for bonding software development teams [1]. For an Englishspeaking developer, character names from Star Trek or Seinfeld are more exciting test data than John Doe, and there is support for this in faking libraries. Hence, the most advanced faking libraries contain data generators for specific languages, idioms, and cultures. These faking libraries are under constant evolution to stay in tune with testing constraints and the testing culture of the time.

Our intuition is that Large Language Models (LLMs) are powerful tools for supporting developers in evolving faking libraries. They are unique systems that possibly encode: 1) domain expertise, 2) testing fluency, and 3) cultural literacy. Domain expertise is key in testing because most interesting data constraints come from the domain. For example, a French mobile phone number generator might output '08 790 60 001'. This would be incorrect, as a French number must start either with '06' or '07', and be split

every two digits, e.g., '06 79 06 00 01'. For test data generators to be usable, they must be executable, and in some cases readily integrated into existing testing frameworks that have conventions. For test fakers to engage developers, they should generate data that is both valid with respect to domain constraints and contains references to their language and culture. Our key intuition is that the generative power of LLMs can help master these three key aspects and be used for the generation of fake test data.

In this paper, we study the original task of using LLMs for producing fake test data. To the best of our knowledge, this promising area has never been studied. We fully implement an approach based on the state-of-the-art LLM from OpenAI. To assess the feasibility of our approach, we curate real-world test data generation scenarios. For example, we can use our approach to generate fake movie character names to be used by a market-leading streaming service in China. We systematically assess the ability of the LLM to generate 1) test data that is fit for testing, and is culturally adequate; 2) executable code that synthesizes fake data; and 3) end-to-end code that is interoperable with state-of-the-art test data fakers.

To evaluate our approach, we have prompted the LLM 63 times to generate test data. We find that our intuition is fully validated: LLMs are indeed able to generate fake test data that is realistic, complies with data constraints, and is readily usable in a testing context. When prompted for executable code and not only data, the LLM produces executable test data generators, ready to be used in test cases. To maximize ease of use and integration within test suites, it is important that the LLM has knowledge about existing faking frameworks: our experiments have also validated this aspect. Finally, we have extensively assessed the qualitative aspects of the generated test data: LLMs are able to capture key cultural dimensions, including language and humor. To sum up, our work demonstrates that LLMs can be used to generate high-quality fake data. Our data and generated fakers are available at https://github.com/ASSERT-KTH/lollm.

Faking Libraries

The goal of a faking library is to generate realistic fake data, which is used as a substitute for real data within software tests. Fakers contain a rich collection of domain and locale-specific data, such as for the generation of user names or the generation of Chinese dishes. The first faker, an open-source library called Data::Faker introduced in 2005, produces fake data to test PERL programs. Its six generators provide data related to companies, dates and times, entities on the Internet such as email or IP addresses, Western names of persons, phone numbers, and US-specific street addresses. Data::Faker is designed to be flexible such that developers can extend it to define custom data generators. Over the years, multiple open-source faking libraries have emerged and are actively developed for all major programming languages, including Ruby, Python, Java, JavaScript, Rust, Haskell, and C++.

In addition to conventional fakers, such as email generators, the developers of faking libraries incorporate data generators with strong cultural and humorous references [1]. When used within a test case, a quote from *Futurama* is likely as effective a string input as is Lorem ipsum text, with the added benefit that it is amusing to a developer who encounters it. Furthermore, good locale support within a faker can be helpful for developers who need test inputs in their native language, or to verify the internationalization of their system.

2. Test Data Generation with LLMs

Testing aims at exercising a software system realistically, without the system being deployed to an actual production environment. Instead of using production values in testing scenarios, developers rely on hard-coded data or fake data produced by so-called test fakers. In this work, we focus on generating test fakers, either in the form of pure data, or in the form of test modules that can be reused by developers to generate test data. In modern development, test fakers are typically provided as reusable faking libraries (see sidebar).

2.1. Overview

Figure 1 summarizes the key steps of our approach for generating fake test data with LLMs. First, we design prompts, which state the testing domain, the cultural constraints, as well as the programming language that

the test generators should harness. We illustrate with a realistic use case for our approach: testing a system for public administration. Such a system requires fake addresses that fulfill country-specific constraints, such as the language for street names or the specificities of postal codes. We propose three types of prompts, with different levels of complexity for the LLM-generated test generators, referred to as M1, M2, and M3. The M1 prompt asks the LLM to directly generate pure test data (e.g., addresses in Lisbon for a rental agency), with no code involved. M2 directs the LLM to generate a program that generates data (e.g., a Java program that generates addresses in Quimperlé for the French tax agency). With M3, we prompt the LLM to generate a program that generates fake data, and that aligns with a specific faking library (e.g., an address generator pluggable within Faker. is, to be used by a real estate company in Boston).

The second step is applicable to the outputs for M2 and M3. Here, we execute the data generator code, as presented in Figure 1. Since the M2 and M3 prompts produce programs that generate data, it is necessary to actually run them to obtain the test data. Finally, the generated test data is used as input data within test cases for the system under test, such as the public administration software system.

2.2. M1: Directly Generate Test Data

In this mode, we use the ability of the LLM to generate pure test data. The outputs of M1 are directly used as inputs to test a software system. The core foundation of M1 is to craft a prompt that states: 1) the application domain of the system under test, 2) the expected natural language and cultural sphere, and, 3) the expected number of items.

For example, the prompt "生成十个中国武汉的假地址。" asks for fake addresses in Wuhan, China, that can be used as test data for the social security system for Wuhan residents. The expected outcome is a list of ten addresses that align with the Chinese address format and district names in Wuhan. Figure 1 presents an equivalent Portuguese prompt for addresses in Lisbon. A test harness takes the generated list of items and feeds it into the system under test.

2.3. M2: Generate Executable Test Data Generators

Beyond raw test data generation, LLMs can also be employed to produce executable code, which can generate random fake testing data. We refer to this mode as M2. This executable code is then integrated by developers to generate fake data into their test

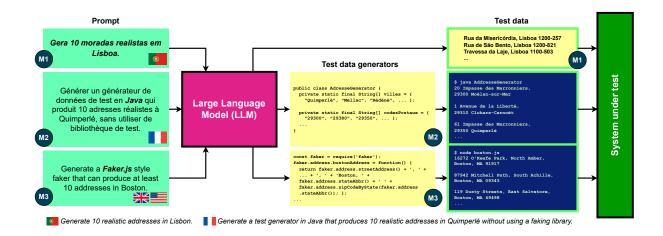


FIGURE 1. Overview of our approach for generating test data generators embedded in application domains and cultural spheres. We design three prompt types with the goal of generating test data. The prompts request for an output formatted as realistic fake data (M1), an automated data generator in a specific programming language (M2), or an automated data generator tailored to a specific faking library (M3). The output of the LLM is either fake data (M1), or a fake data generator (M2, M3). Our culturally diverse team of authors analyzes the adequacy of this output in order to evaluate the ability of the LLM to generate test data that is domain adequate and culturally adequate.

suite. Figure 1 shows an example prompt for M2. The prompt has three main sections. First, a message guides the LLM to "synthesize a test data generator without using any library." Second, the prompt specifies the target programming language in which the data generator should be synthesized, such as "Java". The third component mentions the type and the cultural context of the data that should be generated, e.g., "the program should produce addresses in Quimperlé." M2 prompts leverage the assumed capability of LLMs to 1) understand the testing domain, and 2) generate complete, executable code [2].

2.4. M3: Generate Complete Interoperable Test Fakers

In the M3 mode, we synthesize end-to-end test data generators on top of existing faking libraries (see side-bar). The main motivation for this mode is to minimize the effort of integrating the test generators in a test suite. To that extent, M3 prompts are more effective than M2 prompts. This productivity boost happens thanks to the benefits of software reuse, here in the context of faking libraries.

Figure 1 shows an example prompt used for M3. The prompt asks the LLM to create a test data generator that specifically uses the Faker.js library. It also specifies the type of data that should be produced by the test data generator, such as "10 addresses in Boston".

3. Experimental Methodology

With the three modes of prompting described above, we generate test data and test data generators for various application domains. To this end, we draw upon the diverse backgrounds and expertise of co-authors, and guide GPT-4 to generate test data generators for applications in Chinese, Farsi, Portuguese, Sinhalese, French, Hindi, Spanish, and English. We devise three research questions to evaluate our novel approach of test data synthesis with LLMs:

- **RQ1:** To what extent is the LLM able to generate high quality, domain-adequate data?
- **RQ2:** To what extent is the LLM able to generate executable code that synthesizes fake data?
- RQ3: To what extent is the LLM able to generate end-to-end, interoperable test data fakers?

Our experimental artifacts can be found in https://github.com/ASSERT-KTH/lollm.

3.1. RQ1 Domain adequacy

In this RQ, we assess the ability of the LLM to generate high quality test data that is appropriate for the specified application domain. We manually examine the outputs from the LLM by matching one or several authors' cultural backgrounds, as well as relevance to the application domain. We check that the synthesized fake data is 1) realistic, 2) appropriate with respect to

the semantics of the domain, and 3) contains specific cultural dimensions, if the prompt expects some.

3.2. RQ2 Executability

In RQ2, we assess the ability of the LLM to synthesize executable code that generates fake data. To do that, we write M2 and M3 prompts and run the code produced by the LLM. We check whether this generated code can successfully be executed to completion. We also check for domain adequacy per the rule described in RQ1.

3.3. RQ3 Interoperability

For the final RQ, we evaluate the ability of the LLM to generate accurate, high-quality end-to-end test data fakers with the M3 mode. We start with the same evaluation criteria for adequacy and executability per RQ1 and RQ2. Additionally, we select one open-source project that uses a faking library in its test suite. We replace the original faker with the LLM-generated version. Finally, we run the full test suite of the project to verify that all the tests still pass with the generated fake data.

4. Experimental Results

We have prompted the LLM 63 times, in 8 different natural languages, and within 10 application domains. For the sake of brevity, we focus on a subset of domains and prompts, in each research question. The curious reader can browse our appendix repository for more fake test data generators.

4.1. RQ1: Data Adequacy

When prompting the LLM to generate pure test data, we discover a high level of cultural adequacy in 5 cases, and an absence of adequacy in 2 cases. We now discuss the cultural context and the adequacy of the LLM output for two domains.

4.1.1. Case study: Adequacy of Chinese data for testing a streaming application. Here, we are testing a streaming application, such as Netflix. We prompt GPT-4 to generate ten suitable names for the Chinese TV series My Own Swordsman, using the M1, M2, and M3 prompting modes. Next, three Chinese co-authors assess the generated names with respect to their cultural adequacy. According to our evaluation, all three modes of prompting can instruct GPT-4 to generate 10 fake names for My Own Swordsman. Specifically, the names generated by each prompt align with the background of the show and display full culture adequacy. For

example, eight names from the M1 prompt are suitable for our TV show, such as 风流剑痴, 清风子, and 月影红. From our Chinese analysts' view, 风流剑痴, which means "A handsome swordsman who is crazy for love," is considered the best one, while also being highly consistent with the mix of ancient culture and humor that characterizes the show.

Recently, several Chinese LLMs have been developed by the research divisions of companies such as Baidu and Alibaba. For further evaluation, we employ the same M1 prompt with two Chinese LLMs, ERNIE Bot and Qwen. We find that GPT-4 performs better than these two LLMs. Overall, although GPT-4 is not a Chinese LLM, it is the better choice for Chinese software testers if they want to obtain relevant fake data with respect to Chinese language and culture.

4.1.2. Case study: Adequacy for low-resource languages. In this case study, we are testing a travel application, such as TripAdvisor. We request GPT-4 to generate tourist attractions in Sri Lanka in Sinhalese, with M1 and M2 prompting modes. We observe that the generated results often include non-existent places. The following text presents a generated output where the locations are completely hallucinated: 'අරුගබේ 'අරුගම්බේ කුමැර අවුස විහාරය' , 'අරුගන්බේ කුමැර වෙනිකාව', 'දුක්ඛාගොඩ ලංවය'. We believe that the primary reason for this poor performance lies in the limited training of GPT-4 with Sinhalese text. To produce a more satisfactory output, the model would require training on a large volume of Sinhalese data, which is likely missing in the OpenAI training dataset. Overall, because of poor tokenization and lack of training data in Sinhalese, the generated data is of low quality. This case study highlights the limitation of our approach for low-resource languages. However, for all the other application domains with high-resource languages, we observe strong domain adequacy, including for Chinese, French, Hindi, Portuguese, and Spanish.

Answer to RQ1

LLMs are able to generate high-quality test data. They successfully capture the application domain as well as the cultural and linguistic constraints. This is good since software systems are designed and embedded in countries and cultures all over the world, all tested with the same rigor.

4.2. RQ2: Executability

We now focus on M2 and M3 prompts to evaluate the executability of the code generated by the LLM. We have performed 17 M2 and 25 M3 prompts, and in 29/42 cases, we obtain executable code. We now discuss two interesting case studies.

4.2.1. Case study: Portuguese food and wine pairing. We aim to generate Ruby code that produces random, fake data, to test a food recommendation system such as Vivino. In this context, software developers expect the data to be realistic and correspond to culturally adequate suggestions. Ideally, the data constraints are explicit predicates in code that can be checked. We study the extent to which GPT-4 is able to generate an executable data constraint related to pairings between Portuguese food and wine, using the faker Ruby library (M3).

Listing 1 shows a snippet of the test data generator synthesized by GPT-4 that implements this data constraint. Within Portuguese dining, red wines are typically paired with meat, while white wines are paired with fish. On line 25 of the listing, the wine type is checked at runtime against the food type. The pair is kept if it complies with the wine-pairing constraint. This example shows that the capability of the model is two-fold: 1) it is aware of wine-pairing conventions, and 2) it is able to embed wine-pairing constraints in code. In total, we had success in generating executable faker code, and remarkably also found executable data constraints regarding food and wine types embedded in the generated code.

4.2.2. Case study: Data Constraint in Farsi poetry -Testing applications using right-to-left scripts. In this case study, we are testing a web publishing application that should support right-to-left scripts with constraints on the size of each line. For this, we employ the M2 mode to synthesize executable Java code that generates Farsi poetry in Masnavi style [3]. This type of poetry is written from right-to-left, and the lines of the poem should have approximately the same length. For this experiment, we use the following M2 prompt: "Generate a Java program without using any library that generates Farsi poem in Masnavi style as test data." The result is a Java application that successfully executes and generates two lines in Farsi. 'به یاد کسی میرویم - که در دل کسی میسویم' , and'به یاد آن روزگار - که با خود میبرد هموار' . The text is written in Farsi, which means it is right-to-left as expected. It also consists of lines with almost the same length. One limitation is that the generated text does not follow the rhythmic patterns of Farsi poetry, but we consider this constraint beyond the scope of the considered domain adequacy. Overall, this case study confirms that the LLM is able to generate executable

```
require 'faker
  class PortuguesePairingGenerator
    PORTUGUESE_WINES = {
       'Vinho Verde' => :white,
       'Alvarinho' => :white,
       'Vinho Alentejo' => :red,
       'Porto' => :red,
       'Madeira' => [:red, :white]
    PORTUGUESE_FOODS = {
       'Bacalhau a bras' => :fish,
       'Caldo verde' => :vegetable,
       'Francesinha' => :meat,
       'Arroz de Pato' => :meat.
       Sardinhas assadas' => :fish
    def self.generate
      wine, type = PORTUGUESE_WINES.to_a.sample
      food, food_type = PORTUGUESE_FOODS.to_a.sample
23
      # Pair white wine with fish and red wine with meat
      if (type == :white && food_type == :fish)
          || (type == :red && food_type == :meat)
         puts "Pair the #{wine} wine with #{food}.
      else
         generate
      end
30
    end
31
  end
  # Generate a pairing
  PortuguesePairingGenerator.generate
```

Listing 1. Wine-pairing test data generator, generated by an LLM, with an embedded wine-pairing data constraint. In this example, we prompt GPT-4 to generate Ruby code with method M3: "(...) Please create a custom test data generator that generates wine-pairings between Portuguese wines and Portuguese foods."

code that produces proper Farsi text, which can be useful for testing web applications displaying right-to-left text.

Answer to RQ2

LLMs are able to synthesize ready-to-use programs for generating test data. They are able to reconcile the dual constraints of generating adequate test data in the considered domain, and generating source code that compiles and executes in a given programming language.

4.3. RQ3: Compatibility with Existing Faking Libraries

For this RQ, we prompt the LLM to extend an existing faking library, and integrate this extended library into the test suite of a real-world Java project. We target the test suite of a project called sakai, which is an open-source, feature-rich learning man-

```
// LLM-generated extension of java-faker for Merlin
    ackage com.github.javafaker;
  public class Merlin {
    private final Faker faker;
    protected Merlin(Faker faker) {
       this.faker = faker;
    public String character() {
       return faker.fakeValuesService().resolve(
       "merlin.characters", this, faker);
16
    public String quote() {
       return faker.fakeValuesService().resolve(
       'merlin.quotes", this, faker);
19
  }
20
21
22
  // Excerpt from the ElasticSearchTest class of sakai
23
24
  public class ElasticSearchTest {
    String resourceName =
25
   - faker.name().name() + " key keyboard";
26
  + faker.merlin().character() + " key keyboard";
27
28
29
30
    @Test
    public void testGetSearchSuggestions() {
31
32
      String[] suggestions = elasticSearchService
       .getSearchSuggestions("keyboard", siteId, false);
33
       List suggestionList = Arrays.asList(suggestions);
34
35
       assertTrue(suggestionList.contains(resourceName));
36
```

Listing 2. Lines 1-20: An extension of the java-faker library generated by the LLM to produce characters and quotes from the TV show *Merlin*. Lines 23-37: An excerpt from a test case in the project sakai which uses the java-faker library to generate fake resource names. We replace the existing call to generate fake names (line 26) with names from characters in *Merlin* (line 27).

agement system. sakai already uses the java-faker library in multiple test classes for generating fake names and placeholder text inputs. For example, lines 25 and 26 of Listing 2 show how the faker is used within the test class ElasticSearchTest to generate a fake name for a Resource object, such as Jane Doe key keyboard. Then, this object is used for testing the search implementation within the test case testGetSearchSuggestions (lines 30-36) to obtain search suggestions that contain the strings key and keyboard from an ElasticSearch service. The assertion on line 35 verifies that the suggestion list includes the recently created resource name, Jane Doe key keyboard.

We prompt the LLM in M3 mode to generate a java-faker-style generator that produces character names and quotes from the TV show *Merlin*. Per our

expectations, the LLM generates code that follows the structure of the <code>java-faker</code> library, specifically a faker class called <code>Merlin.java</code> (lines 1 to 20 in Listing 2), and a <code>merlin.yml</code> file containing character names and quotes. Moreover, the two generated files follow the same pattern as the existing generators within <code>java-faker</code>. Next, we extend <code>java-faker</code> with these two new files, and replace the existing <code>java-faker</code> version in <code>sakai</code> with this extended version. We update the test class <code>ElasticSearchTest</code> to generate fake names from characters in <code>Merlin</code>, as illustrated on lines 26 and 27 of Listing 2. Finally, we compile the project and execute the test suite, which now uses this extended faker.

Within the class ElasticSearchTest, 3 test cases call the LLM-generated faker, and 5 assertions assess behavior using this fake data. We observe that the complete end-to-end integration works seamlessly: 1) the test suite compiles and runs, and 2) all the test cases successfully pass with the extended java-faker library. From a testing perspective, using a resource called Uther Pendragon from the generated Merlin faker is as effective as using a conventional "Jane Doe" resource. This is strong evidence that the LLM is capable of successfully generating fakers that are ready to be used by developers, while engaging them even more with their tasks.

Answer to RQ3

LLMs encode knowledge about popular faking libraries, used to test thousands of software projects. This knowledge can be leveraged to generate new fakers, directly interoperable with test suites. To the best of our knowledge, our paper is the first to bridge the creative power of LLMs and the hard engineering constraints of data faking.

5. Related Work

Large Language Models have found application in various phases of software engineering, from the generation of specifications to the maintenance of legacy software [2]. Yet there are caveats to the use of LLMs in software engineering tasks, owing to their unpredictability, and issues such as potential data leakage [4]. Ouyang et al. [5] highlight that the non-determinism of LLMs can negatively impact code generation, producing semantically and syntactically different, potentially incorrect, code based on hyperparameter configurations. In the same vein, Poesia et al. [6] propose an approach to enforce constraints on the code generated by LLMs, including syntax and variable typing. In this paper, we leverage the creative

power of LLMs to synthesize wide-ranging test data, and their programming power to produce executable test data generators.

Several studies have experimented with LLMs and machine learning models as tools to aid software testing, including the automated generation of unit tests [7]. MockSniffer [8] uses machine learning to recommend components that may be substituted by mocks within unit tests. QTypist [9] uses LLMs to generate context-aware text inputs for testing mobile application interfaces. Tan and colleagues explore the use of Recurrent Neural Networks (RNNs) [10] and LLMs [11] for generating synthetic, representative test data for the Norwegian national population registry. Generative Adversarial Networks (GANs) have been used to anonymize test data used in the healthcare domain [12]. Similar to these studies, we utilize LLMs to automatically produce realistic synthetic test data. A core novelty of our work is the use of LLMs in the context of fakers, to automatically generate executable code that produces test data.

Many researchers have explored the cultural (in)adequacies exhibited by LLM outputs. Cao and colleagues [13] discover that ChatGPT performs poorly in non-American contexts. Naous et al. [14] analyze the cultural adaptability of LLMs, concluding that Arabic LLMs default to Western cultures. Chen et al. [15] report on the inadequate performance of several LLMs in understanding Chinese humor, including the detection of punchlines. In this work, we have explored diverse dimensions of cultural adequacy within test data. While the LLM performs very well at data generation, we observe that cultural adequacy varies depending on the task and the language used for prompting.

6. Conclusion

In this paper, we have addressed the original problem statement of generating test data generators with LLMs. To validate this far-reaching idea, we have performed an in-depth study into the capabilities of LLMs for generating test data, with attention to both hard software testing requirements and soft cultural requirements such as cultural adequacy. Our experimental results clearly indicate that current LLMs are able to succeed in this task. Over 63 prompts, we successfully obtain a large majority of good data generators, that can execute and produce valuable test data. As a final proof-of-concept, we integrate an LLM-generated data faker in the test suite of a mature and well-tested Java project. The complete success of this PoC shows that LLM-generated test fakers can

support serious and engaging software testing. Overall, our research opens a promising avenue for the use of generative models for generating data that is both adequate for testing and is culturally relevant.

7. REFERENCES

- D. Tiwari, T. Toady, M. Monperrus, and B. Baudry, "With Great Humor Comes Great Developer Engagement," in 2024 IEEE/ACM 46th International Conference on Software Engineering: Software Engineering in Society (ICSE-SEIS), IEEE, 2024.
- I. Ozkaya, "Application of large language models to software engineering tasks: Opportunities, risks, and implications," *IEEE Software*, vol. 40, no. 3, pp. 4–8, 2023.
- 3. W. M. Thackston, A millennium of classical Persian poetry: a guide to the reading & understanding of Persian poetry from the tenth to the twentieth century. Ibex Publishers, Inc., 1994.
- J. Sallou, T. Durieux, and A. Panichella, "Breaking the Silence: the Threats of Using LLMs in Software Engineering," in 2024 IEEE/ACM 46th International Conference on Software Engineering: New Ideas and Emerging Results (ICSE-NIER), IEEE, 2024.
- S. Ouyang, J. M. Zhang, M. Harman, and M. Wang, "Llm is like a box of chocolates: the non-determinism of chatgpt in code generation," arXiv preprint arXiv:2308.02828, 2023.
- G. Poesia, O. Polozov, V. Le, A. Tiwari, G. Soares, C. Meek, and S. Gulwani, "Synchromesh: Reliable code generation from pre-trained language models," arXiv preprint arXiv:2201.11227, 2022.
- M. Schäfer, S. Nadi, A. Eghbali, and F. Tip, "An empirical evaluation of using large language models for automated unit test generation," *IEEE Transactions on Software Engineering*, 2023.
- H. Zhu, L. Wei, M. Wen, Y. Liu, S.-C. Cheung, Q. Sheng, and C. Zhou, "Mocksniffer: Characterizing and recommending mocking decisions for unit tests," in *Proceedings of the 35th IEEE/ACM Interna*tional Conference on Automated Software Engineering, pp. 436–447, 2020.
- Z. Liu, C. Chen, J. Wang, X. Che, Y. Huang, J. Hu, and Q. Wang, "Fill in the blank: Context-aware automated text input generation for mobile gui testing," in 2023 IEEE/ACM 45th International Conference on Software Engineering (ICSE), pp. 1355–1367, IEEE, 2023.
- R. Behjati, E. Arisholm, M. Bedregal, and C. Tan, "Synthetic test data generation using recurrent neural networks: a position paper," in 2019 IEEE/ACM 7th International Workshop on Realizing Artificial Intel-

- ligence Synergies in Software Engineering (RAISE), pp. 22–27, IEEE, 2019.
- C. Tan, R. Behjati, and E. Arisholm, "Enhancing synthetic test data generation with language models using a more expressive domain-specific language," in *IFIP International Conference on Testing Software* and Systems, pp. 21–39, Springer, 2023.
- E. Piacentino and C. Angulo, "Generating fake data using gans for anonymizing healthcare data," in *International Work-Conference on Bioinformatics and Biomedical Engineering*, pp. 406–417, Springer, 2020.
- 13. Y. Cao, L. Zhou, S. Lee, L. Cabello, M. Chen, and D. Hershcovich, "Assessing cross-cultural alignment between chatgpt and human societies: An empirical study," *arXiv preprint arXiv:2303.17466*, 2023.
- 14. T. Naous, M. J. Ryan, and W. Xu, "Having beer after prayer? measuring cultural bias in large language models," *arXiv preprint arXiv:2305.14456*, 2023.
- Y. Chen, Z. Li, J. Liang, Y. Xiao, B. Liu, and Y. Chen, "Can pre-trained language models understand chinese humor?," in *Proceedings of the Sixteenth ACM Inter*national Conference on Web Search and Data Mining, pp. 465–480, 2023.

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