Automated Prompt Generation for REST API Test Amplification Using LLMs

Scope description

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Abstract—With the recent release of the Restats coverage tool for REST APIs, evaluating test coverage from a black-box approach has become possible. The thesis aims to leverage this tool to train a model that associates test cases with the most effective prompts, using large language models like ChatGPT. The main goal is to amplify tests from given test suites and OpenAPI documentations to improve overall coverage. Additionally, the model will provide insights for prompt engineering, helping to refine the most effective prompts for improved amplification and coverage output.

1. Introduction

Writing tests for a REST APIs is very time-consuming for developers [1]. Recently, standardized REST API coverage criteria for black-box testing were established by Lopez et al. [2]. These metrics enabled the development of a tool called Restats [3]. Using the tool, it allows for quantitatively measuring the coverage of REST API test cases using a black-box approach. This brings the idea that Restats can also be used as part of evaluating a model during training to associate the best prompt for a given test case. If the coverage increases after test amplification, it would be assumed that an existing test suite has improved with the added test(s), and that a specific prompt proved to be a success in amplification. Looking at the API documentation of tools like ChatGPT, we can find that it allows us to set a randomness temperature on generated output. This can be experimented on in two ways:

- Keeping randomness would increase the diversity of generated test cases, allowing for greater exploration with unsuccessfully generated tests.
- 2) Eliminating randomness would increase predictability, allowing for greater understanding of the effectiveness of specific prompts.

Another recent study, also by Lopez et al. [4], compared a white-box approach (EvoMaster [5]) with a black-box approach (RestTestGen [6]) for generating tests. They observed that a combination of black-box and white-box yielded the best results in terms of code coverage and fault finding. A combination of both approaches can be realized in this thesis by including both OpenAPI documentation and/or source code in the prompts.

2. Relevance

Multiple ways have been developed for generating REST API test cases, which means generating tests from scratch. One such tool is RestTestGen [6], it generates test cases for REST APIs from OpenAPI specifications using a black-box approach. EvoMaster [5] takes it a step further by using a white-box approach, and generates test cases using specific algorithms. Because of the white-box approach, EvoMaster evaluates the code using code coverage (statement and branch coverage), independent from the coverage evaluation proposed by Lopez et al. [2]. A downside of this tool is that it requires more manual work, in the sense that the user has to write their own class that extends the one in their library.

To the best of my knowledge, no tools have been developed that perform test amplification for REST APIs: generating tests from existing ones. Previous state-of-the-art tools generate tests from scratch. It has been discussed that adding new tests based on existing ones, can make the test generation process more targeted and cost-effective. On the one hand, the test generation process can be geared towards achieving a specific engineering goal better based on how existing tests perform with respect to the goal. [1]

From previous research utilizing LLMs for test amplification, using only 3 prompts has already shown to be successful for amplifying tests [7]. Training a model that can associate the best prompt from a large set of prompts for a given code snippet could prove to be very powerful. Another benefit is that it could reveal valuable insights for prompt engineering for future research.

3. Research Question

The research question that I will focus on during the thesis is the following:

How can a prompt generation model be trained to amplify REST API tests using LLMs, where they increase REST API coverage from a black-box approach?

4. My qualifications for the thesis

I specialize in Data Science and AI, making my background well-suited to the requirements of the thesis. In addition, I have taken a course in Software Engineering and Software Reengineering, which has provided me with a deep understanding of the importance of tests in software development and maintenance. Through the reengineering course, I learned various software design patterns and techniques [8] that will be useful in reengineering the Restats tool.

Furthermore, I have completed a course in Reinforcement Learning. This could prove to be useful in designing and training the model that can generate effective prompts, and improve REST API test coverage through feedback loops.

5. Challenges and approaches

5.1. Semi-automated REST API coverage tool

The Restats tool at present is only semi-automated and relies on external tools:

- tool 1 (e.g. Postman): Can be used to generate OpenAPI specifications. Automating this process is not a huge priority, but would be a nice addition to save some time.
- tool 2 (e.g. Burp Suite): Used as a proxy between the testing framework and REST API. These interactions are logged and bumped to HTTP requests and responses in text format, which is required as input for the Restats tool.

Before training of the model can even be considered, the tool will need to be reengineered as soon as possible. I will try to do this with minimal code change. The biggest time-consumer is generating HTTP dumps, which I will try to automate.

5.2. Projects for training

Obtaining large, diverse projects with defined OpenAPI documentation which the coverage tool needs as input, could be a challenge. Luckily, it is possible to convert Postman Containers to OpenAPI documentation.

5.3. Initial prompts for training

Training the model would need initial prompts to pick the most suited one for a given test case. These will have to be manually written. To save time, performing data augmentation is ideal. I propose to use 2 sets of prompts, and have each prompt from each set form a pair with the other set. This means that given 2 sets of prompts A and B, we'd produce:

$$\#prompts = |A| \times |B|$$

Given a mere 10 prompts in each set, this would mean that 100 prompts of initial training data will be augmented.

For example:

- Prompt 1 in set A:
 "Play the role of an experienced software tester for REST APIs and perform test amplification."
- Prompt 2 in set B:
 "Here is the test case: **test case** and here is the full OpenAPI specification: **specification**."

Combining various prompts could give interesting insights in when specific prompts perform the best and why.

6. Planning

I made a rough plan that I will try to follow. The plan can of course change during the year:

| Phase | | Period |
|-------|----------------------------|-----------------------------|
| 1) | Literature study | October - December 14th |
| 2) | Restats tool reengineering | December 14th - January 7th |
| 3) | Training data collection | January 7th - January 21th |
| 4) | Implementation | January 21th - March 14th |
| 5) | Evaluation | March 14th - April 7th |
| 6) | Thesis | April 7th - June |

Figure 1. Thesis plan

In the first phase, I continue with my literature study to get a better view of what was already tried, and upon what I can improve on.

The second phase will be very important. The current tool lacks automation, so it will require reengineering as soon as possible to fit my needs.

The third phase will involve finding suitable projects to train the model on, and prompt engineering to obtain initial prompts

The fourth phase will revolve around implementing and evaluating the model. In the evaluation, an interesting comparison

In the fifth phase, the model will be evaluated by comparing

it to popular tools such as EvoMaster and RestTestGen. Another interesting comparison could be applying the tool on the same projects as in a related paper [7] and observing whether the model managed to give the same or even better prompts.

The final phase will be about writing my thesis.

References

- Benjamin Danglot, Oscar Vera-Perez, Zhongxing Yu, Martin Monperrus, and Benoit Baudry. The emerging field of test amplification: A survey. *CoRR*, abs/1705.10692, 2017.
- [2] Alberto Martin-Lopez, Sergio Segura, and Antonio Ruiz-Cortés. Test coverage criteria for restful web apis. In Proceedings of the 10th ACM SIGSOFT International Workshop on Automating TEST Case Design, Selection, and Evaluation, A-TEST 2019, page 15–21, New York, NY, USA, 2019. Association for Computing Machinery.
- [3] Davide Corradini, Amedeo Zampieri, Michele Pasqua, and Mariano Ceccato. Restats: A test coverage tool for restful apis. In 2021 IEEE International Conference on Software Maintenance and Evolution (ICSME), pages 594–598, 2021.
- [4] Alberto Martin-Lopez, Andrea Arcuri, Sergio Segura, and Antonio Ruiz-Cortés. Black-box and white-box test case generation for restful apis: Enemies or allies? In 2021 IEEE 32nd International Symposium on Software Reliability Engineering (ISSRE), pages 231–241, 2021.
- [5] Andrea Arcuri. Evomaster: Evolutionary multi-context automated system test generation. In 2018 IEEE 11th International Conference on Software Testing, Verification and Validation (ICST). IEEE, April 2018.
- [6] Emanuele Viglianisi, Michael Dallago, and Mariano Ceccato. Resttest-gen: Automated black-box testing of restful apis. In 2020 IEEE 13th International Conference on Software Testing, Validation and Verification (ICST), pages 142–152, 2020.
- [7] Tolgahan Bardakci, Serge Demeyer, and Mutlu Beyazıt. Test amplification for rest apis using large language models.
- [8] Serge Demeyer, Stephane Ducasse, and O Nierstrasz. Object-Oriented Reengineering Patterns. The Morgan Kaufmann Series in Software Engineering and Programming. Morgan Kaufmann, Oxford, England, July 2002.