TDD Without Tears: Towards Test Case Generation from Requirements through Deep Reinforcement Learning

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Test-driven development (TDD) is a widely-employed software development practice that mandates writing test cases based on requirements *before* writing the actual code. While writing test cases is the centerpiece of TDD, it is time-consuming, expensive, and often shunned by developers. To address these issues associated with TDD, automated test case generation approaches have recently been investigated. Such approaches take source code as input, but not the requirements. Therefore, existing work does not fully support true TDD, as actual code is required to generate test cases. In addition, current deep learning-based test case generation approaches are trained with one learning objective, i.e., to generate test cases that are exactly matched with the ground-truth test cases. However, such approaches may limit the model's ability to generate different yet correct test cases. In this paper, we introduce PyTester, a Text-to-Testcase generation approach that can automatically generate syntactically correct, executable, complete, and effective test cases while being aligned with a given natural language requirement. We evaluate PyTester on the public APPS benchmark dataset, and the results show that our Deep RL approach enables PyTester, a small language model, to outperform much larger language models like GPT3.5, StarCoder, and InCoder. Our findings suggest that future research could consider improving small over large LMs for better resource efficiency by integrating the SE domain knowledge into the design of reinforcement learning architecture.

CCS Concepts: • Computing methodologies \rightarrow Artificial intelligence; Natural language processing; • Software and its engineering \rightarrow Software development techniques.

ACM Reference Format:

1 INTRODUCTION

TDD is an agile software development practice [8] that advocates the creation of test cases before code development [4, 7]. The methodology comprises iterative steps of creating test cases, writing code to pass the test cases, and refactoring. Thus, developers can conceptualize the specification before coding, which increases developers' productivity [16]. Therefore, writing high-quality software test cases is crucial for TDD. However, writing test cases is a time-consuming part of TDD. To address this issue, previous studies proposed various automated test case generation approaches

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XXXX-XXXX/2018/1-ART \$15.00

to automatically generate test cases based on random [40, 41], search algorithms [17, 35], and deep learning [1, 55, 59] techniques.

Nonetheless, there are two main limitations to the previous approaches. *First*, existing test case generation approaches often take code as input, which is not applicable to TDD, as TDD mandates writing test cases *before* writing code. *Second*, existing test case generation approaches often aim to generate test cases that exactly match the ground truth test cases, without considering alternative test cases, their characteristics (i.e., syntax correctness, executability, and completeness) of test cases, and importantly, the alignment of the test cases to the given requirement.

In this paper, we propose PyTester, a Text-to-Testcase generation approach for Python using Deep Reinforcement Learning. Our Deep RL-based model is optimized with Proximal Policy Optimization (PPO) on a reward function that considers three types of feedback, namely, syntax correctness, test executability, and code coverage. We evaluate our approach on four evaluation aspects, i.e., syntax correctness, test completeness measured by code coverage, test effectiveness measured by mutation score, and requirement alignment. Evaluating the alignment of the test cases to a given requirement is indeed challenging. To address this challenge, we define that a test case is aligned with a given requirement if the test case is executable (i.e., all assertions are passed.) with the ground truth code, assuming that the ground truth code is the correct implementation of the given requirement. Then, we compare our PyTester with four strong large language models (LLMs), namely, CodeT5-large[33], GPT3.5[38], StarCoder [34], and InCoder [18]. Through a comprehensive experiment on the APPS benchmark dataset [22], we address the following research questions:

(RQ1) What is the performance of PyTester for the Text-to-Testcase generation task when compared to the state-of-the-art models?

Of the test cases generated by PyTester, 99% are syntactically correct, 84% are aligned with the requirements while achieving a code coverage of 80% and a mutation score of 61%, which outperforms all of the studied LLMs. This finding demonstrates that a smaller language model like PyTester can outperform larger language models when carefully designed. Importantly, after being optimized with deep reinforcement learning, PyTester outperforms GPT3.5 for all evaluation metrics, highlighting the effectiveness of our deep reinforcement learning framework for Text-to-Testcase generation.

(RQ2) How does the choice of the feedback types impact the performance of our PyTester? The top-3 reward functions for our PyTester are the Syntax+Coverage, Syntax+Executability, and Syntax-only types of feedback. Without considering syntax correctness, model performance decreases by 3-13%, indicating that syntax correctness must be the minimum consideration when designing a reward function for deep reinforcement learning in the Text-to-Testcase generation task.

(RQ3) What types of runtime errors occur in the PyTester-generated test cases?

As low as 15.59% of the PyTester-generated test cases are incorrect. Among the incorrect test cases, PyTester mostly encounters an Assertion Error issue for 10.75%, followed by other types of errors (i.e., IndexError, ValueError, EOFError, SyntaxError).

These results lead us to conclude that the performance of smaller language models like PyTester is not necessarily inferior to that of large language models if carefully designed. Our results confirms that Deep Reinforcement Learning substantially contributes to performance improvements. Deep RL enables smaller language models, with the smallest model parameter size and the fastest inference times by *at least* one order of magnitude, to outperform much larger language models. Furthermore, our findings indicate that incorporating test case characteristics into the reward function significantly enhances performance, resulting in the model generating test cases that are 44% more aligned with the requirement with 44% higher code coverage and 32% higher mutation

score when compared to the GPT3.5 large language model. Finally, these findings emphasize the importance of considering domain knowledge and test case characteristics when designing an RL-based Text-to-Testcase generation approach.

Novelty & Contributions. The novelty and contributions of this paper are as follows:

- We, *conceptually*, introduce PyTester, a Text-to-Testcase generation approach that can automatically generate syntactically correct, executable, complete, and effective test cases while being aligned with a given natural language requirement.
- We, *technically*, formulate the Text-to-Testcase generation task as a deep reinforcement learning problem where the reward function is designed to consider various characteristics of test cases, including syntax correctness, test executability, and code coverage.
- We, *empirically*, demonstrate that our PYTESTER model outperforms all of the studied state-of-the-art Large Language Models including GPT3.5, StarCoder, and InCoder, while being the smallest language model with the quickest inference time.

To support the open science initiatives and increase the verifiability of our study, the replication package of PyTester is available at https://github.com/tddpytester/pytester.

Paper Organization. The paper is organized as follows. Section 2 describes the background and motivation of our study. Section 3 presents our PyTester approach. Section 4 presents the experimental setup and the model experimentation. Section 5 discusses the results to answer our research questions. Section 6 discusses related work about reinforcement learning in software engineering. Section 7 discloses the threats to validity. Section 8 draws the conclusion.

2 BACKGROUND AND MOTIVATION

In this section, we describe the background of TDD, discuss existing automated test case generation approaches, and a motivating example of using ChatGPT for Text-to-Testcase generation.

2.1 Test-Driven Development (TDD)

Test-Driven Development (TDD) [4, 7] is a software development methodology that involves writing tests for a piece of code before actually implementing the code itself. Aligned with the Shift-Left Testing principles and Agile manifesto [3, 8], TDD is typically carried out in small, incremental steps, with the developer ① writing a failing test based on requirements, then ② writing the minimum amount of code required to make the test pass, and finally ③ refactoring the code as needed. With TDD, developers need to first understand the requirements and think about the expected behavior of their code, leading to more reliable and maintainable code. Prior studies also found numerous benefits of TDD, including increasing requirements understanding [37], producing more clean code with a higher number of test cases [16, 26]. However, the process of writing test cases is still manual, time-consuming, and labor-intensive. This limitation highlights the need for an automated test case generation approach based on a given requirement, which likely speeds up the TDD process and improves developers' productivity.

2.2 Automated Test Case Generation Approaches

Various automated test case generation approaches are proposed with different techniques.

Random-based test case generation (Randoop), proposed by Pacheco et al. [40, 41], aims to automatically create unit tests for Java classes using feedback-directed random test generation. However, the generated test cases are still suboptimal (e.g., miss edge cases or fail to cover specific scenarios) and non-deterministic (e.g., produce different sets of test cases from different runs).

Search-based test case generation (e.g., Evosuite [17] for Java and Pynguin [35] for Python) leverages evolutionary search algorithms to guide the search for suitable test cases to produce test

suites that achieve high code coverage. However, prior studies raised concerns that the test cases generated by search-based approaches are often not meaningful [2] and ineffective [19, 42].

Deep learning-based test case generation (e.g., ATLAS [59], Athena [55], and A3Test [1]) formulated the task as a Neural Machine Translation (NMT) problem (Java Method→Test). However, such DL-based approaches aim to generate test cases that are exactly matched with the ground truth test cases, without considering the alternative test cases.

Limitations. While different test case generation approaches are proposed, none of these approaches are designed for TDD (i.e., taking requirement as input), are not able to generate test cases without code (i.e., mostly they take code as input), are mostly designed for Java—not Python, the dynamic type programming language. Therefore, these limitations highlight the need for an automated test case generation approach that takes a requirement as input and can generate alternative test cases beyond the ones that exactly match the ground truth test cases.

2.3 ChatGPT for Text-to-Testcase Generation: Motivation

ChatGPT [38] is a powerful AI conversational large language model (LLM) designed for generating natural text based on a given prompt question in a dialogue style. Recently, researchers found that ChatGPT can perform very well in various software engineering tasks [23], including code generation [12] and test case generation [46, 50, 54, 60, 61]. For example, Chen et al. [12] proposed CodeT, a code generation approach based on a heuristic ranking process using a dual execution agreement of ChatGPT-generated codes and test cases. Schäfer et al. [46] proposed TestPilot, a ChatGPT-based test case generation approach for JavaScript based on a given input function. Siddiq et al. [50] investigated the performance of LLMs for test case generation based on a Java focal method (i.e., methods to be tested). Similarly, many recent work [54, 60, 61] also investigated the performance of ChatGPT-based test case generation for a given Java focal method.

While ChatGPT has been widely used for test case generation, existing work only focuses on taking code as input—not the requirements as input. Therefore, existing test case generation approaches do not support TDD, as TDD mandates writing test cases based on requirements before writing the actual code. In addition, a systematic literature review by Hou et al. [23] also confirmed that test case generation approaches to support TDD (i.e., LLM-based Text-to-Testcase generation) remain largely unexplored. To address this research gap, we first conduct a preliminary analysis to empirically investigate the performance of ChatGPT for Text-to-Testcase generation.

An Illustrative Example. We use ChatGPT through the OpenAI API by selecting the recommended *GPT-3.5-turbo* model endpoint.¹ Following the prompt engineering's best practices² and Chen et al. [12], we design a prompt that includes the context (i.e., external information or additional context that can steer the model to better responses) and the instruction (i.e., a specific task or instruction that the model should perform). Figure 1 (left) presents an example of the input format (i.e., prompt format) where the context refers to the signature of the Python function with a natural language requirement in the docstring, without the code implementation (Figure 1 (top right)), while the instruction refers to a natural language comment "# check the correctness of the '...' function" followed by an incompleted assert statement. We randomly select one programming task (Problem #4479) from the testing set of the APPS dataset [22] as an illustrative example. Note that a comprehensive evaluation of ChatGPT is provided in Section 5 where we found that our PyTester performs better. For the given Problem #4479, we reformat the data structure into a triplet of <function signature + requirement text, code implementation, test cases>. Then, the function

¹The experiment was run in June 2023.

²https://www.promptingguide.ai/

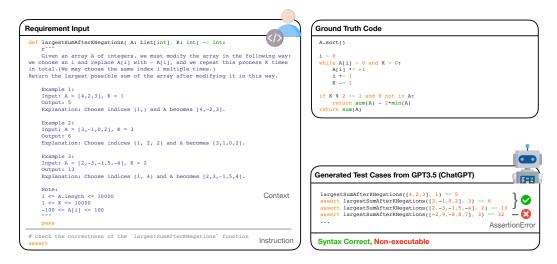


Fig. 1. An example of test cases generated by the OpenAl's GPT3.5 model based on a given requirement input. Syntax correctness is measured by an AST parser, while the test executability is measured by running the test cases against the ground truth code.

signature + *requirement text* is input into ChatGPT to generate test cases, while *code implementation* is only used to evaluate if the generated test cases can be run against the ground truth code.

Observation-1: ChatGPT can generate syntactically correct test cases, yet some of the generated test cases cannot be executed (i.e., failed test cases). In reality, when using ChatGPT to generate test cases based on a given requirement, it becomes challenging to verify if the generated test cases are correct and aligned with the given requirement or not. To address this challenge, assuming that the ground truth code is the correct implementation, we execute the test cases against the ground truth code to verify if the ChatGPT-generated test cases are executable or not. Figure 1 (bottom right) shows that four test cases generated by ChatGPT are syntactically correct, but the fourth test case is not executable. In particular, the fourth test case is generated with the test input of '([-2,9,-8,8,7], 3)'. Thus, the expected output should be '30', but incorrectly generated as '32'. Therefore, this test case will raise an *AssertionError*. Such syntactically correct, yet non-executable test cases indicate that the test case is still not aligned with the given requirements. This observation demonstrates that ChatGPT is able to generate syntactically correct test cases, yet fails to generate executable ones (i.e., not aligned with the requirements).

Observation-2: When ChatGPT generates non-executable test cases, it becomes challenging to evaluate the completeness and effectiveness of the test cases. Intuitively, effective test cases should exercise all lines of code in the program (i.e., achieving high code coverage), and be able to discover bugs/defects when the program is slightly changed (i.e., the same set of test cases is able to catch the introduced bugs). Code coverage is widely used to measure test completeness [1, 17, 40, 46, 50, 54, 55]. Thus, a higher code coverage percentage often increases the confidence that the software behaves as intended. However, studies [11, 21] argue that code coverage only measures the extent to which the test cases exercise the lines of code in the program, but not the effectiveness of the test cases. Therefore, mutation testing is proposed to evaluate the effectiveness of the test cases [11, 28, 36, 43]. Mutation testing aims to introduce intentional faults (mutations) into the code and check if the existing test cases can detect these faults (mutants)—
referring to the fault detection capability of the test cases. Thus, the mutation score is measured as a

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percentage based on the number of mutants that are killed (i.e. detected by the test cases) versus the total number of mutants introduced. Despite the importance and benefits of code coverage and the extensive research on mutation testing in the literature, we found that, both code coverage and mutation score have not been taken into consideration by existing techniques on ChatGPT-based test case generation.

Summary. TDD offers numerous benefits to software development, yet is time-consuming and expensive. Existing automated test case generation approaches do not yet support TDD practices (i.e., code, not requirements, is treated as input). Our motivating analysis also shows that ChatGPT (the most powerful language model) still generates non-executable, incomplete, and ineffective test cases, hindering the adoption of ChatGPT and other LLMs for Text-to-Testcase generation in practice. To support TDD practices, this observation highlights the urgent need for a novel automated test case generation approach that is able to generate syntactically correct, executable, complete, and effective test cases.

PYTESTER

Aim. We introduce PyTester, a Text-to-Testcase generation approach that aims to automatically generate syntactically correct, executable, complete, and effective test cases based on a given natural language requirement. We formulate the Text-to-Testcase generation task as a Reinforcement Learning (RL) problem due to the following reasons:

- To increase models' ability to generate alternative test cases. Traditionally, supervised finetuning approaches are trained to generate test cases that are textually and exactly matched with the ground truth test cases. Thus, these models can only generate test cases based on what the model had seen in the training data, limiting the model's ability to generate test cases outside of the domain (i.e., out-of-distribution (OOD) problems [49]). In fact, the ground truth test cases may not be representative of all of the possible test cases. Thus, alternative test cases with different test inputs that still satisfy the given requirement should also be considered as valid.
- To incorporate test case characteristics into the feedback loop. Traditionally, the generated test cases are evaluated only on their similarity with the ground truth test cases. However, in real-world practices, developers normally design test cases by ensuring test cases are syntactically correct, executable, and complete. Such test case characteristics are critically important, yet remain largely disregarded by the existing DL-based test case generation approaches.

PyTester leverages a Deep Reinforcement Learning (Deep RL) framework, which is a combination of deep learning and reinforcement learning principles. In the context of the Text-to-Testcase generation, the goal of RL is to enable the agent (i.e. the Text-to-Testcase generation model) and its policy (the brain of the agent) to learn by interacting with the environment (through trial and error) and receiving rewards (negative or positive) as

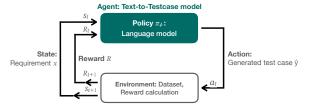


Fig. 2. The formulation of Text-to-Testcase generation as a Reinforcement Learning problem.

feedback for performing actions (i.e. gener-

ating test cases). This formulation enables PyTester to (1) learn autonomously through interaction with their environment without ground truth test cases, allowing the models to generate alternative test cases and (2) learn how to generate syntactically correct, executable, complete, and effective test cases while being aligned with a given requirement through a carefully-crafted reward function rather than a basic loss function used in traditional finetuning models.

3.1 Our Reinforcement Learning Framework for Text-to-Testcase Generation

We represent the reinforcement learning problem as a Markov Decision Process (MDP) which decomposes scenarios as a series of states, connected by actions and associated with a specific reward. Following Figure 2, we define and explain each of the components below.

Language Model: Given the natural language *requirement x* and a *testcase y*, the Text-to-Testcase generation language model is defined as $P(y|x) = \prod_{i=0}^{m} p_{\theta}(y_i|x, y_{0:i-1})$

Dataset: We define a training dataset \mathcal{D} of size M, which contains triplets of < requirement, code, test cases> as $\mathcal{D} = \{(x^i, c^i, y^i)\}_{i=1}^{i=M}$. The requirement x consists of a signature of the Python function, the natural language requirement included in the docstring, the hidden code implementation (pass), the instruction prompt as a natural language comment "# check the correctness of the '...' function", and an incompleted assert statement "assert". On the other hand, the ground truth test case y consists of an assertion statement.

Agent/Policy: Our policy π_{ϕ} is defined as a language model p_{θ} , training from dataset \mathcal{D} . The policy outputs the probability of all vocabularies conditioned on the current state: $\pi_{\phi}(\cdot|s_t)$.

State: A state $s_t = (x, \hat{y}_{0:t-1})$ is defined as a concatenation of the **requirement** x and the **test** case tokens $\hat{y}_{0:t-1}$ generated so far.

Action: An action $a_t = \hat{y}_t \sim \pi_{\phi}(\cdot|s_t)$ is a token sampled from the policy. The action is then used as a continuation of the current state by the **transition function**, T, to produce the next state, s_{t+1} . Specifically, the next state is the concatenation of the action and the current state: $s_{t+1} = T(s_t, a_t) = (x, \hat{y}_t)$, where $\hat{y}_t = a_t \oplus \hat{y}_{0:t-1}$.

With the Markov Decision Process (MDP), our PyTester agent is learned as an episodic task. Generally, an episode is a sequence of interactions between the agent and environment starting from an initial state so and ending at a terminal state where the agent will receive the reward and update the policy. At the beginning of each episode, the *initial state* will start from a requirement xsampled from the Dataset \mathcal{D} , denoted as $s_0 = x \sim \mathcal{D}_x$. Then, our policy π_ϕ takes a requirement x as input to generate a test case \hat{y} that is syntactically correct, executable, and complete. Technically, the policy π_{ϕ} will sequentially generate a sequence of tokens \hat{y}_i for the test case \hat{y} until reaching the *end* of the trajectory (i.e., after generating the EOS token or reaching the maximum generation length). Then, the generated test cases \hat{y} are input into the interactive environment to receive a reward via a Reward Calculation function $R(x, \hat{y})$, which returns a cumulative **reward point**. The reward will be provided if the generated test cases are syntactically correct, executable against the ground truth code (i.e., aligned with the requirements), and complete (i.e., achieving high code coverage). On the other hand, the penalty will be provided if the generated test cases are syntactically incorrect and non-executable (e.g., runtime errors like incorrect method names and assertion errors like wrong test inputs). Finally, the policy π_{ϕ} is learned over time in order to maximize a reward function written as:

$$\mathcal{J}(\pi_{\phi}) = \mathbb{E}_{x \sim \mathcal{D}_{x}, \hat{y} \sim \pi_{\phi}(\cdot \mid x)} R(x, \hat{y})$$
(1)

Overview. Figure 3 presents an overview of our PyTester framework. Our framework consists of two steps: policy training and policy optimization. In the *policy training* step, we aim to build the

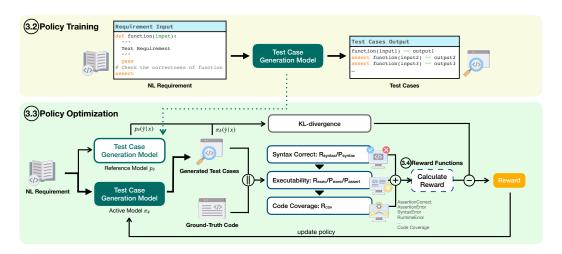


Fig. 3. An overview of our Deep Reinforcement Learning framework for the Text-to-Testcase Generation task (called PyTester). || denotes a concatenation, + denotes an addition, and – denotes a subtraction.

agent (i.e., the Text-to-Testcase Generation model) where its policy interacts with the environment (i.e., the input dataset) and learns to make decisions (i.e., generate test cases) over time. However, currently, the agent is still suboptimal as it is trained to generate the same test cases as the ground truths in a supervised manner. Thus, the *policy optimization* step aims to further optimize the agent via a reward function through Deep Reinforcement Learning. To do so, given an environment (i.e., a triplet of <*requirement*, *code*, *test cases*> in the training dataset), the agent will take requirement as input into the model in order to perform an action (i.e., generate test cases), where the test cases will be evaluated via a reward function. Our reward function is designed to incorporate three aspects of test case characteristics, namely syntax correctness, test executability, and test completeness. The agent is optimized with Proximal Policy Optimization (PPO) [48] using our reward function, and stabilized with KL-divergence [32]. Below, we describe the technical details of policy training, policy optimization, and our reward function.

3.2 Policy Training

The ultimate goal of the policy training is to build a language model with some preliminary knowledge of the relationship between the requirement and its associated test cases. Therefore, we adopt the *default CodeT5-large* as our language model [33, 44]. To ensure that the model performs well on a target task (i.e., Text-to-Testcase generation), we finetune our language model with the training dataset. Given a training dataset $\mathcal{D} = \{(x^i, c^i, y^i)\}_{i=1}^{i=M}$, we finetune the language model to learn the mapping between the requirement x and its corresponding test cases y (not the ground truth code y) in order to minimize the multi-class cross-entropy loss $\mathcal{L}_{\text{FT}} = -\mathbb{E}_{(x,y) \sim \mathcal{D}} \log p_{\theta}(y_n|x,y_{0:n-1})$, y0 where y1 is the maximum length of the test cases. Then, the loss is optimized using an Adam

3.3 Policy Optimization

Next, we further update the PyTester policy with a reward function through reinforcement learning. At the initial state, we initiate two finetuned language models from the policy training step: a language model policy π_{ϕ} as our active model (i.e., to-be trained model) and a language model p_{θ}

optimizer [29] (the hyperparameters settings are provided in the Appendix).

as a reference model (i.e., the frozen model that is not updated during the policy optimization step). We optimize our policy using PPO and KL-divergence as follows.

Proximal Policy Optimization (PPO) [48]. We use PPO to improve the training stability of the policy optimization process. Formally, PPO optimizes the following surrogate objective:

$$\mathcal{J}_{\text{surr}}(\pi_{\phi}) = \min(rA^{\pi_{\phi}} \text{old}(x, \hat{y}), \text{clip}(r, 1 - \epsilon, 1 + \epsilon)A^{\pi_{\phi}} \text{old}(x, \hat{y})), \tag{2}$$

where
$$r = \frac{\pi_{\phi}(\hat{y}|x)}{\pi_{\phi_{\text{old}}}(\hat{y}|x)},$$
 (3)

in which ϵ is a small positive scalar indicating how much the policy can be updated and $\pi_{\phi_{\text{old}}}$ is the policy that collects the data. $A^{\pi}(x,\hat{y})$ is the advantage function of a policy π given a state-action (i.e., input text requirement - output test cases) pair (x,\hat{y}) , and is computed by the Generalized Advantage Estimator (GAE) [47].

KL-divergence [32]. Following best practices [39, 52, 62], we utilize the Kullback-Leibler (KL) divergence regularization [32] to stabilize the training process. KL-divergence is a penalty to prevent our active model π_{ϕ} from exploring too differently from the reference model p_{θ} (i.e., the finetuned model). Concretely, we define the KL-divergence as $KL_{penalty}$ and the reward function R as

$$R(x, \hat{y}) = R_{\text{task}} - KL_{\text{penalty}} = R_{\text{task}} - \beta \log \frac{\pi_{\phi}(\hat{y}|x)}{p_{\theta}(\hat{y}|x)},\tag{4}$$

where R_{task} is the summation of the rewards and $\beta > 0$ is a hyperparameter controlling the strength of the regularization.

3.4 Reward Functions

Once the test cases \hat{y} are generated from the model, the generated test cases are evaluated against our reward function. Our reward function aims to consider three types of feedback, namely, syntax correctness, test executability, and test completeness. In general, each reward function will provide a reward point for positive feedback or a penalty point for negative feedback. Our policy is optimized based on the following reward function:

$$R_{task} = R_{syntax} + R_{exec} + R_{cc} - P_{syntax} - P_{exec} - P_{assert}$$
 (5)

Below, we define the three types of feedback as follows:

Syntax Correctness Feedback concerns the syntactically correctness of the generated test cases \hat{y} . To determine if the generated test cases are syntactically correct, we use the Python ast library³ to parse the generated test cases \hat{y} . We define Condition $\mathbb{1}_{syntax(\hat{y})} = 1$ if \hat{y} is syntactically correct (i.e., successfully parsed by AST). Then, the feedback is provided to the policy based on the following reward/penalty function given reward/penalty point (r_{syntax}, p_{syntax}):

$$R_{syntax} = \mathbb{1}_{syntax} r_{syntax},\tag{6}$$

$$P_{syntax} = (1 - \mathbb{1}_{syntax}) p_{syntax}, \tag{7}$$

Test Executability Feedback concerns the functional correctness of the generated test cases \hat{y} given the ground truth code c. To determine if the generated test cases are executable and functional correct to the ground truth code, we use the built-in function exec.⁴ Specifically, we decompose the executability feedback into two conditions: Execution Condition $(\mathbb{1}_{exec(c,\hat{y})})$ and Assertion Condition $(\mathbb{1}_{assert(c,\hat{y})})$. We define Condition $\mathbb{1}_{exec(c,\hat{y})} = 1$ if the execution of (c,\hat{y}) does not raise a

³https://docs.python.org/3/library/ast.html

⁴https://docs.python.org/3/library/functions.html#exec

RuntimeError (i.e., the test cases are executable) and Condition $\mathbb{1}_{assert(c,\hat{y})}=1$ if the execution does not raise an AssertionError (i.e., execution passes all the generated assertion test cases). Then, the feedback is provided to the policy based on the following reward/penalty function given reward/penalty point (r_{exec} , p_{exec} , p_{assert}):

$$R_{exec} = \mathbb{1}_{syntax} \mathbb{1}_{exec} \mathbb{1}_{assert} r_{exec}, \tag{8}$$

$$P_{exec} = \mathbb{1}_{syntax}(1 - \mathbb{1}_{exec})p_{exec},\tag{9}$$

$$P_{assert} = \mathbb{1}_{syntax} \mathbb{1}_{exec} (1 - \mathbb{1}_{assert}) p_{assert}$$
 (10)

Code Coverage Feedback concerns the percentage of the line of code (LOC) in ground truth code c tested by generated test cases \hat{y} . To determine the percentage, we use coverage.py⁵ to calculate the code coverage, denoted by $CodeCoverage(c, \hat{y})$, which has a value range of [0, 100]. Then, the feedback is provided to the policy based on the following reward function given a normalized $CodeCoverage(c, \hat{y})$ as reward point (r_{cov}) :

$$R_{cov} = \mathbb{1}_{syntax} \mathbb{1}_{exec} \mathbb{1}_{assert} r_{cov}$$
 (11)

4 EXPERIMENTAL SETUP

In this section, we present the motivation of our three research questions and describe our experimental setup for evaluating our PyTester approach and the baselines.

(RQ1) What is the performance of PyTester for the Text-to-Testcase generation task when compared to the state-of-the-art models?

Motivation. Prior studies found that large language models (e.g., GPT3.5) tend to outperform smaller language models for various SE tasks [38, 45]. However, little is known about whether our PyTester which is based on a smaller language model like CodeT5 will outperform large language models.

(RQ2) How does the choice of the feedback types impact the performance of our PYTESTER? Motivation. The reward function plays an important role in providing a positive/negative signal to the agent if the action satisfies the goal. There exist multiple variations of the reward functions (e.g., considering all types of feedback or considering only one type of feedback). Yet, little is known about which types of feedback are most important.

(RQ3) What types of runtime errors occur in the PyTester-generated test cases?

Motivation. Our PyTester approach may generate both correct and incorrect test cases. Thus, a manual analysis of the incorrectly generated test cases may offer opportunities for future researchers to consider improving the performance of our approach. Yet, little is known about what are the most common types of runtime errors that are found in the incorrectly generated test cases by PyTester.

4.1 Studied Dataset

The APPS benchmark dataset [22] is used to evaluate our approach and compare it with the baseline approaches. The APPS benchmark dataset consists of 10,000 programming tasks with 131,777 associated test cases collected from Codewars, AtCoder, Kattis, and Codeforces. The dataset consists of three difficulty levels of the programming tasks, including the introductory level, the interview level, and the coding competition level. Each of the programming tasks consists of triplets of <a requirement, an associated code, and associated test cases>. We note that, in this study, only the APPS benchmark dataset is suitable for our Text-to-Testcase generation task since our PyTester model requires a large enough size of the dataset for policy training. Thus, other datasets

⁵https://coverage.readthedocs.io/en/7.2.7/

like MBPP [5] and HumanEval [13] are not considered in this experiment, as they are specifically designed for code generation, they are considered relatively small when compared to the APPs benchmark dataset, and are mainly designed for evaluating the zero-shot LLMs, not our Deep RL model. Similar to prior studies [22], we use the same dataset splitting of 5,000 samples for training and 5,000 samples for testing.

4.2 Data Preprocessing

The quality of the dataset may have an impact on the performance of PyTester. Thus, we carefully craft the dataset for model training through our data preprocessing as follows.

Data Reformatting. After manual analysis, we found that, in the APPS dataset, different programming tasks have different approaches to test case execution. In particular, some programming tasks are tested with an assert statement format (assert add(1,1) == 2), while some are tested with a standard input-output format (python add.py 1 1 2). Thus, it becomes challenging for a DL model to automatically handle such inconsistency. In particular, for such programming tasks with the standard input-output format, the method name does not exist and the assert statements are missing. To address this challenge, for programming tasks written in a standard input-output format, we transform them by giving a function name to the programming task, then adding a test method (e.g., def test_main()) to be called by assert statements (see an example in Figure 4). Finally, all of the programming tasks in the dataset will have a consistent format of assertion calls.

Data Filtering. In addition, we found that not all samples in the dataset are of high quality. Common issues include missing test cases, missing code solutions, and non-executable test cases. Since the goal of PyTester is to generate test cases that are aligned with the requirement, our selection criteria are defined as the test cases that must exist and be executable against the code solution. After the data filtering step, our training dataset consists of 3,401 samples and our testing dataset consists of 3,259 samples.

4.3 Evaluation Metrics

Since the goal of PyTester is to generate syntactically correct, executable, complete, and effective test cases that are aligned with the requirement, our evaluation will focus on the following four aspects: syntax correctness, requirement alignment, code coverage, and mutation score.

- **Syntax Correctness** measures the percentage of the generated test cases that are syntactically correct. The syntax correctness is defined by the ast Python library. The given test case is considered syntactically correct if the AST can be successfully run.
- Requirement Alignment measures the percentage of the generated test cases that are aligned with the requirement. Since the ground truth code is the correct implementation of the requirement, any test cases that can be successfully executed against the ground truth code are considered correct (i.e., correctly align with the given requirement and call the correct functions to be tested with the right test inputs and the expected outputs). Thus, we define that a test case is aligned with a given requirement if the test case is executable with the ground truth code. To do so, we execute the concatenation of the ground truth code with the generated test cases using the exec built-in function.⁷
- Code Coverage measures the completeness of the generated test cases for a given requirement. Ideally, in addition to aligning with the requirements, the test cases must be complete

⁶https://docs.python.org/3/library/ast.html

 $^{^7} https://docs.python.org/3/library/functions.html \# exec$

(i.e. executing all lines of the ground truth code solution). Thus, we measure the line-level code coverage of the generated test cases using the coverage.py Python library.⁸

• Mutation Score measures the effectiveness of the generated test cases. High-quality test cases must be able to detect bugs if the code is slightly changed. Mutation testing aims to introduce intentional faults (mutations) into the code and check if the existing test cases can detect these faults (mutations). Then, the mutation score is measured as a percentage based on the number of mutations that were killed (detected) versus the total number of mutations introduced. We use the MutPy Python library⁹ to measure a mutation score with a timeout of 10 seconds per sample.

Different from prior studies that aim to generate test cases that are textually and exactly matched with the ground truth test cases, we neither use such an exact match nor a code similarity measure (e.g., a BLEU score) in this study.

4.4 Baselines

Since the existing test case generation approaches (discussed in Section 2) are not designed for TDD (i.e. do not take a requirement as input), it becomes challenging to fairly compare our PyTester with the existing ones. Since prior studies demonstrated that Large Language Models (LLMs) could be a viable solution for various SE tasks, we consider the following four baseline models.

- CodeT5-large (770M parameters) [33] is a transformer language model pre-trained on six programming languages of CodeSearchNet [24] with the masked span prediction task [58].
- InCoder (6.7B parameters) [18] is a transformer-based LLM pre-trained on a total of 159GB public code with permissive open source licenses from GitHub and GitLab, in which 52GB are Python, and a total of 57GB of text content are from StackOverflow.
- **StarCoder** (15.5B parameters) [34] is a transformer-based LLM pre-trained on 80 different programming languages and natural languages such as GitHub issues, commits, and notebooks. We use the finetuned version which is trained with 35B Python tokens.
- **GPT-3.5** (175B parameters¹⁰) [38] is one of the most powerful state-of-the-art LLMs developed by OpenAI, which is a transformer-based LLM pre-trained with the next token prediction task on the internet and the third-party licensed data, then finetuned using Reinforcement Learning from Human Feedback (RLHF) [14]. We chose the recommended *gpt-3.5-turbo* endpoint, which was accessed in June 2023.

4.5 Model Experimentation

The performance of our PyTester model heavily relies on the design of our reward function. Thus, considering three different types of feedback, we perform an experiment with the following seven variations:

- Syntax-only $(p_{syntax}=-2, r_{syntax}=2)$
- Executability-only (p_{exec} =-2, p_{assert} =-0.3, r_{exec} =2)
- Coverage-only $(p_{exec}=-2, r_{cov}=norm([0, 2]))$
- Syntax+Executability (p_{syntax} =-2, p_{exec} =-1, p_{assert} =-0.3, r_{exec} =2)
- Syntax+Coverage $(p_{syntax}=-2, r_{cov}=norm([0, 2]))$
- Executability+Coverage (p_{exec} =-2, p_{assert} =-0.3, r_{exec} =2, r_{cov} =norm([0,2]))
- Syntax+Executability+Coverage $(p_{syntax}=-2, p_{exec}=-1, p_{assert}=-0.3, r_{exec}=2, r_{cov}=norm([0, 2]))$

⁸https://coverage.readthedocs.io/en/7.2.7/

⁹https://pypi.org/project/MutPy/

¹⁰GPT-3.5 model size is not reported publicly. The previous version (GPT-3 model[10]) has a model parameter size of 175B.

where r is the reward point, and p is a penalty point, or 0 if not specified. For example, when considering 'Syntax-only' as a reward function, a reward point of 2 is given if the generated test cases are syntactically correct, otherwise, a penalty point of -2 is given. We run our experiment on two NVIDIA GeForce RTX 3090 GPUs with 24 GB vRAM, an Intel(R) Core(TM) i9-9980XE CPU @ 3.00GHz with 36 core processors, and 64G RAM. The hyperparameter settings for the policy training and the policy optimization are reported in Table 1 and Table 2, respectively.

In total, we conducted an experiment with 7 variations. During the training phase, we set the model to learn to generate multiple assert statements (without the length limit). During the inference phase, the test case generation for each model uses a beam search of 5 and each model is evaluated using the following measure, called TestCaseScore:

$$TestCaseScore = \frac{(2 \times CodeCoverage \times MutationScore)}{(CodeCoverage + MutationScore)}$$
(12)

TestCaseScore is a harmonic mean of the code coverage and the mutation score. After the comprehensive experiment, we find that **the PyTester model performs best when it is trained to generate multiple assert statements with a reward function considering both Syntax and Coverage feedback**, which we used as a reference setting for our PyTester model for the remainder of the paper.

Table 1. The hyperparameter settings of PyTester during the policy training step.

Table 2. The hyperparameter settings of PyTester during the policy optimization step.

Hypernarameter

Value

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Hyperparameter	Value	Learning rate	1e-5
Learning rate	2e-5	KL coefficient	0.2
Warmup steps	1000	VF coefficient	0.01
Weight decay	0.01	Clip-range	0.05
Batch size	2	Clip-range value	0.2
Gradient accumulation steps	4	Batch size	8
Learning rate scheduler type	inverse_sqrt	Mini batch size	4
Epoch	20	Gradient accumulation steps	4
	,	Epoch	1

5 RESULTS & DISCUSSION

(RQ1) What is the performance of PyTester for the Text-to-Testcase generation task when compared to the state-of-the-art models?

Table 3. (RQ1) The performance of PyTester when compared to state-of-the-art LLMs.

Model	Model	Inference	Syntax	Requirement	Code	Mutation
	Parameters	Time	Correctness	Alignment	Coverage	Score
PyTester	770M	<1 hr	99.42%	84.41%	80.98%	61.45%
Finetuned CodeT5-large	770M	<1 hr	65.08%	35.56%	34.44%	26.94%
InCoder	6B	250 hr	4.63%	0.03%	0.03%	0.03%
StarCoder	15.5B	40 hr	96.78%	71.56%	69.07%	54.32%
GPT3.5	175B	12 hr	98.90%	40.20%	37.43%	29.00%

<u>Results.</u> Of the test cases generated by PYTESTER, 99% are syntactically correct, 84% are aligned with the requirements while achieving a code coverage of 80% and a mutation

score of 61%, which outperforms all of the studied LLMs. Table 3 presents the performance of PyTester when compared to the state-of-the-art LLMs according to the four evaluation metrics. When comparing PyTester with GPT3.5, our PyTester model is able to generate test cases that are 1% more syntactically correct, 44% more aligned with the requirement, 44% more complete, and 32% more effective in the shortest amount of inference time due to the smallest size of the model. This finding indicates that a small language model like PyTester which is based on CodeT5 does not necessarily perform worse than large language models if they are carefully designed. Instead, by incorporating the domain knowledge of software testing into the architecture of PyTester (i.e., the consideration of test case characteristics in the reward function that is largely ignored by existing LLM models), PyTester is able to perform better than large language models, with a smaller size of the model parameters and a shorter amount of inference time. This highlights the significant novelty of our approach contributing to the research area of Text-to-Testcase generation.

Our proposed DeepRL framework can improve the requirement alignment percentage by 49%, the code coverage by 47%, and the mutation score by 32% when compared with the CodeT5 base model. Table 3 shows that, without the deep reinforcement learning, the CodeT5 base model performs worse than GPT3.5, which is aligned with the common intuition and prior studies [20, 38]. On the other hand, when adding deep reinforcement learning to the CodeT5 base model, our experiment confirms that the PyTester model performs better than the GPT3.5 for all evaluation metrics. This finding highlights the importance of our proposed deep reinforcement learning framework for the Text-to-Testcase generation task.

Figure 4 presents an illustrative example of the requirement input and the test cases by PyTester and the baselines. This example depicts a programming task (Problem ID #569) in the APPS dataset. We observe that PyTester can generate test cases that are syntactically correct and align with the requirement while achieving high code coverage and high mutation score. On the other hand,

- GPT3.5 and StarCoder can generate syntactically correct test cases, but some are non-executable, raising an AssertionError. We observed that the non-executable test cases have to do with incorrect test inputs and incorrect expected outputs. For example, StarCoder generates a test input with a missing of the first value (e.g., "2\n"), while GPT3.5 generates the expected outputs of the test case with an additional "\n". Such incorrectly generated test cases could be due to the lack of consideration of the requirement alignment during the learning process of the large language models. In contrast, the consideration of syntax correctness and code coverage in the reward function of PyTester improves the generated test cases to align to the given requirement (i.e., executable) with high code coverage.
- InCoder often generates incorrect test cases (syntactically incorrect, non-executable, low code coverage, and low mutation score). Like in this example, some issues include the missing of an assert call, the incorrect test inputs/outputs, and the incompleted generation. Such incompleted generation happens since InCoder does not generate the terminal tokens (i.e., the EOS token), resulting in a longer inference time and incompleted assert statements.
- CodeT5-large often generates repetitive assert statements. For example, this assert statement "assert test_main('2\nba') == '1'" is repeatedly generated two times, while the last assert statement is also incomplete. Such repetitive generation has to do with the traditional learning objective aiming to generate test cases that are exactly matched with the ground truth test cases. Differently, PyTester addresses this challenge by considering the test case characteristics during the test case generation. Rather than evaluating the test cases with a traditional text similarity measure, we instead consider the test case characteristics via a reward function.

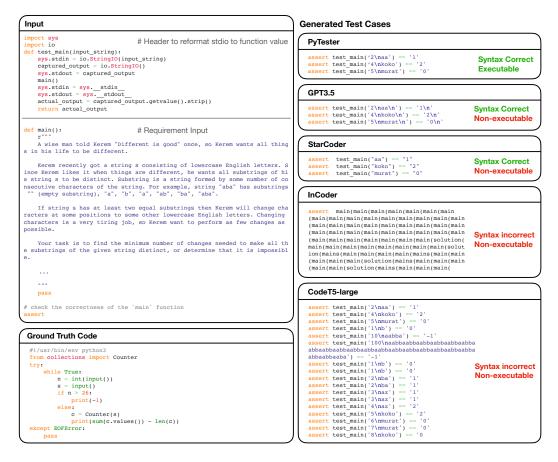


Fig. 4. An example of test cases generated by PYTESTER and other baseline approaches (depicted from Problem ID #569 of the testing dataset).

(RQ2) How does the choice of the feedback types impact the performance of our PyTester?

Table 4. (RQ2) The performance of our PyTester for the 7 variations of the reward functions. **S**: Syntax, **E**: Executability, **C**: Coverage.

Reward	Syntax	Requirement	Code	Mutation	TestCase
Function	Correctness	Alignment	Coverage	Score	Score
S-only	99.39%	82.72%	79.47%	60.96%	69.00%
E-only	96.26%	75.73%	72.95%	56.34%	63.58%
C-only	98.59%	86.87%	81.96%	56.47%	66.87%
S+E	98.80%	83.49%	80.34%	61.25%	69.51%
S+C	99.42%	84.41%	80.98%	61.45%	69.87%
E+C	94.57%	67.78%	65.37%	51.01%	57.31%
S+E+C	98.80%	81.68%	78.34%	58.76%	67.15%

Results. The top-3 reward functions for PyTester are the Syntax+Coverage, Syntax+Executability, and Syntax-only types of feedback. Table 4 presents the performance of our PyTester for the seven variations of the reward functions. We find that the Syntax+Coverage, Syntax+Executability, and Syntax-only types of the reward function achieve a comparative Test-CaseScore of 69.87%, 69.51%, and 69.00%, respectively. On the other hand, without considering the syntax correctness feedback (for the remaining reward function types), the TestCaseScore of PyTester is decreased by 3-13%. This finding highlights the importance of syntax correctness in the reward function—i.e., such feedback will greatly help the agent to generate test cases that are syntactically correct during the policy optimization step. This finding suggests that syntax correctness must be the minimum consideration when designing a reward function for deep reinforcement learning in the text-to-test case generation task.

In addition, we also find that both Syntax+Coverage and Syntax+Executability mostly perform best (i.e., highly correlated). For Syntax+Coverage, the model aims to directly generate syntactically correct test cases that achieve high code coverage, enabling the generated test cases to be executable against the ground truth code. On the other hand, for Syntax+Executability, the model aims to directly generate syntactically correct test cases that are executable against the ground truth code, enabling the generated test cases to achieve high code coverage. Therefore, considering either Syntax+Coverage or Syntax+Executability in the reward function is the best. Nevertheless, the lowest-performing variation of our PyTester still outperforms GPT3.5 and other LLMs.

(RQ3) What types of runtime errors occur in the PyTester-generated test cases?

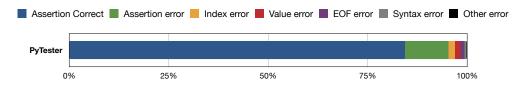


Fig. 5. (RQ3) The common types of runtime errors that occur in the PyTester-generated test cases.

<u>Results.</u> Among the incorrectly generated test cases, PYTESTER mostly encounters an Assertion Error issue for 10.75%. Despite PYTESTER performing the best when compared to the studied LLMs, we want to gain deeper insights into the incorrectly generated test cases. As mentioned in Table 3, we find that 84.41% of the test cases generated from PYTESTER are aligned with the requirements (the blue color in Figure 5), meaning that 15.59% of the generated test cases are not executable, thus incorrect. Thus, we conduct an analysis to investigate what are the common types of runtime errors that occur in the PyTester-generated test cases. As shown in Figure 5, PyTester encounters the following top five common types of errors as follows:

- Assertion Error (10.75%) is an exception that is raised when an assert statement fails. The AssertionError is raised when the actual output (i.e., the output of the generated assertion) does not match the expected output (i.e., the output from the ground truth code). This finding highlights that as low as 10.75% of the generated test cases are not executable (i.e., are not aligned with the requirement). Therefore, future researchers should consider developing a novel mechanism integrated into the RL framework to improve the requirement alignment.

model incorrectly generates the test case as "assert test_main('13\ngogmgogogogo') == '***gmg***'. The highlighted character indicates the missing character that is not generated by PyTester, leading to the incorrect access of the index in the sequence, thus, throwing an IndexError exception.

- Value Error (1.35%) is an exception that occurs when a function or operation receives an input that has the correct data type but is not in the expected range or does not have a valid value. For example, in Problem ID #911, the model should generate the test case as "assert test_main('3 2 \n50 85 250\n10 15 25') == 'Limak'", but the model incorrectly generates the test case as "assert test_main('3 \n2\n1 1\n2 3') == '2\n0 points'". The Value Error is related to the highlighted character where it should receive two input values, but one of the values is missing, thus, throwing a ValueError exception.
- EOF Error (0.98%) is an exception that occurs when a built-in function like input() or a method like readline() of a file object encounters an unexpected end of file (EOF) condition while trying to read input or data. For example, in Problem ID #1152, the model should generate the test case as "test_main('3 3\n0 1 0\n0 1 0\n1 0 0\n1 0

6 RELATED WORKS

In this section, we highlight the difference in our work with respect to the literature on reinforcement learning in software engineering.

Reinforcement learning (RL) [53] is a machine-learning approach where an agent learns to map observations to actions by maximizing numerical reward functions. Prior studies have demonstrated successes in various tasks ranging from recreation games [9, 25, 51, 56] to real-world nuclear fusion plasma control [15]. Recently, RL has been applied to text generation tasks. Specifically, LLMs utilize RL to train models based on user preferences through human feedback (RLHF) [14]. Consequently, LLMs can exhibit complex and coherent behaviors such as instruction following [39], summarization [52], stylistic continuation [62], and conversation [27].

In software engineering, reinforcement learning has been adopted in the code generation tasks [33, 57] to improve the compilability and execution rate of the generated code. For example, Wang *et al.* [57] proposed CompCoder, an RL approach that considers compiler feedback in the reward function to generate more compilable code. Le *et al.* [33] proposed CodeRL, an actor-critic [6, 31] deep reinforcement learning framework for code generation.

Different from prior studies, we formulate the Text-to-Testcase task as a deep reinforcement learning problem. Results also show that our PyTester outperforms other LLMs, highlighting the novelty and the significance of our work that contributes to the area of Text-to-Testcase generation.

7 THREAT TO VALIDITY

In this section, we disclose the threat to the validity of our study.

Threats to construct validity. The policy training and the policy optimization steps of our PyTester involve hyperparameter settings (see Table 1 and Table 2). Prior studies raised concerns that different hyperparameter settings may impact the performance of the Deep RL models [30]. However, the parameter optimization is beyond the scope of this paper. Thus, future research can consider exploring the impact of the hyperparameter settings on the Deep RL models.

Threats to internal validity. The variation of the reward function may impact the performance of PyTester. However, our RQ2 confirms that, among the 7 variations, the performance varies between 57.31% and 69.87% of the TestCaseScore. Despite the high difference in the performance among the reward functions, we find that the lowest-performing variation of our PyTester still outperforms LLMs. Thus, the reward function does not pose a threat to the validity of our study. Nevertheless, our study is limited by one scheme of reward points (ranging from -2 to 4). However, finding an optimal scheme of reward points is beyond the scope of this work. Thus, future research is encouraged to explore the impact of the reward points on the performance of Deep RL models.

Threats to external validity. The experiment of this paper is limited to the APPS benchmark dataset, the Python programming language, and the context of the online programming tasks. Thus, the results may not be generalized to other datasets, programming languages, and contexts. Thus, future research is encouraged to explore the generalizability of our Pytester in other contexts.

8 CONCLUSION

In conclusion, we propose PyTester, a Text-to-Testcase generation approach for Python using Deep Reinforcement Learning via a reward function that considers three types of feedback, namely, syntax correctness, test executability, and code coverage. Through a comprehensive experiment on the APPS benchmark dataset [22], we find that:

- Of the test cases generated by PyTester, 99% are syntactically correct, 84% are aligned with the requirements while achieving a code coverage of 80% and a mutation score of 61%, which outperforms all of the studied LLMs.
- The top-3 reward functions for our PyTester are the Syntax+Coverage, Syntax+Executability, and Syntax-only types of feedback.
- As low as 15.59% of the PyTester-generated test cases are incorrect. Among the incorrectly generated test cases, PyTester mostly encounters an Assertion Error issue for 10.75%, followed by other types of errors (i.e., IndexError, ValueError, EOFError, SyntaxError).

Based on these results, we draw the following implications for future research.

- The performance of smaller language models is not necessarily inferior to that of large language models if carefully designed. Training or finetuning large language models often requires significant computational resources, including powerful hardware and large datasets, with the assumption that more resources and more datasets will contribute to performance improvement [20, 38]. This paper takes a different direction from the existing work by using Deep RL to enable smaller language models, with the smallest model parameter size (770M) and the fastest inference times by at least one order of magnitude, to outperform much larger language models (175B). This finding suggests that future research could consider improving small over large LMs for better resource efficiency.
- The SE domain knowledge should be considered when designing a deep reinforcement learning architecture. The performance of many AI models often relies on its model architecture. Thus, many prior studies often adopted various data mining and optimization techniques to improve such AI models. Different from existing work, this paper takes an alternative direction by integrating the SE domain knowledge when designing the reinforcement learning architecture (i.e., incorporating test case characteristics into the reward function).

This enables PyTester to generate test cases that are more syntactically correct, executable, complete, and effective while being aligned with a given requirement.

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