Can LLMs Generate Reliable Test Case Generators?
A Study on Competition-Level Programming Problems

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Abstract

Large Language Models (LLMs) have demonstrated remarkable capabilities in code generation, capable of tackling complex tasks during inference. However, the extent to which LLMs can be utilized for code checking or debugging through test case generation remains largely unexplored. We investigate this problem from the perspective of competition-level programming (CP) programs and propose **TCGBench**, a *Benchmark for (LLM generation of) Test Case Generators*. This benchmark comprises two tasks, aimed at studying the capabilities of LLMs in (1) generating valid test case generators for a given CP problem, and further (2) generating targeted test case generators that expose bugs in human-written code. Experimental results indicate that while state-of-the-art LLMs can generate valid test case generators in most cases, most LLMs struggle to generate targeted test cases that reveal flaws in human code effectively. Especially, even advanced reasoning models (e.g., o3-mini) fall significantly short of human performance in the task of generating targeted generators. Furthermore, we construct a high-quality, manually curated dataset of instructions for generating targeted generators. Analysis demonstrates that the performance of LLMs can be enhanced with the aid of this dataset, by both prompting and fine-tuning. Code is available at `https://github.com/TCGBench/TCGBench`.

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1 Introduction

Code generation is one of the most important tasks for large language models (LLMs). With the advancement of model performance, LLMs have demonstrated remarkable capabilities across various code-related tasks [Li et al., 2022a, Jiang et al., 2024]. The common method for evaluating code generation tasks involves testing with test cases, primarily because code correctness is typically determined through execution. Consequently, the ability to find and correct code errors is an important skill for human coders. These errors are not only syntax errors but also need reasoning based on code semantics or specific details. Therefore, verifying code correctness by generating test cases holds significant importance.

This leads us to consider: do models possess the capability to verify code correctness by generating test cases? We approach this question from the perspective of competition-level programming (CP) problems. These problems are effective for testing a model's reasoning ability in relatively short contexts and have been widely used since they are crafted by experts for wide-ranging competitions and education. In parallel with the evolution of reasoning models, a growing body of work has begun to focus on evaluating language model capabilities through their use [Jain et al., 2025, DeepSeek-AI et al., 2025, Qwen et al., 2025]. We observe that within these evaluation efforts [Jain et al., 2025, Team et al., 2025], researchers utilize LLMs to automatically generate test case generators. However, the process for generating generators is either overly simplistic or lacks a thorough analysis regarding the reliability of the data generated by the models.

On the other hand, while advanced reasoning models have demonstrated significant capabilities on CP problems, some work [Huang et al., 2024] suggests that models may exhibit a tendency towards memorizing solutions rather than performing true reasoning. The extent to which models genuinely comprehend the semantics of code also represents a question warranting attention. Furthermore, the precise scope of language models' generation capabilities in this domain remains under-researched.

To systematically investigate this problem, we propose a novel benchmark, TCGBench, a *Benchmark for (LLM generation of) Test Case Generators*. The contributions of our work are as follows:

- We collect 208 problems from two representative CP problem data sources, along with over a thousand corresponding standard solver programs and erroneous programs. Utilizing this data, we propose two evaluation tasks designed to evaluate the capability of models in generating test case generators, specifically evaluating their ability to produce valid generators and targeted generators.
- We create a carefully curated, high-quality dataset of code analysis for writing targeted generators. Our analysis indicates that LLMs can achieve improved performance by using this dataset for prompting and fine-tuning.

2 Benchmark Building

2.1 Problem Data Source

We use competition-level programming (CP) problems as our data source. These problems are effective for testing a model's reasoning ability in relatively short contexts and have been widely used since these problems are crafted by experts for wide-ranging competitions and education, and the correctness of code generated by LLMs is easy to verify.

We select two representative problem sets, utilized to train human competitive programmers, as our data source. Our data comes from two representative problem sets used to train programmers for competitions.

The NOIP Problem Set. The NOIP Problem Set includes problems from the National Olympiad in Informatics in Provinces (NOIP), the contest of China's National Olympiad in Informatics for adolescents. The term 'province' in the name of this problem set indicates that the associated competition is conducted simultaneously nationwide, organized on a provincial basis, and utilizes identical test problems across the country. The problems in this competition are often inspired by real-life scenarios or well-defined mathematical tasks, with relatively lower difficulty in comprehension. We select the NOIP problems from 1998 to 2022 to serve as our initial problem set.

Problem Statement

Implement an Aho-Corasick (AC) automaton. Given a text string S and n pattern strings $T_{1\sim n}$. For each pattern string T_i, determine how many times it appears in S.

For 100% of the data, $1 \le n \le 2 \times 10^5$, the total length of $T_{1\sim n}$ does not exceed 2×10^5, and the length of S does not exceed 2×10^6.

Valid Test Case Generator

```python
while len(patterns) < n and current_length < total_length_T:
    pattern_length = random.randint(1, min(20, total_length_T - current_length))
    pattern = generate_randomstring(pattern_length)
    patterns.append(pattern)
    current_length += pattern_length
S = generate_string(S_length)
inputs = [str(n)] + patterns + [S]
```

Erroneous Solver Program

```cpp
struct AhoCorasick
{
    std::vector<Node> t; // An AC automaton has several nodes.
    AhoCorasick(){
        init();
    }
    void init() {
        t.assign(2, Node());
        t[0].next.fill(1); // next: the links in the AC automaton
        t[0].len = -1;// len: the length of the string
        // that maps with the path from the root to the current node.
    }// ...
```

Target Instruction

The core issue in the implementation stems from incorrectly initializing the root node's transition table to point to node 1, rather than 0. ...

To generate a test case that makes the code fail, we need to create input where:

1. Use pattern strings where the short patterns are the suffix or prefix of the longer ones. (e.g. a,ab,cab,abc)

2. The text string contains repeated overlaps of these patterns.

Successful Targeted Generator

```python
for _ in range(n):
    length = random.randint(1, 10)  # Pattern length ranging from 1 to 10
    pattern = ''.join(random.choices(string.ascii_lowercase, k=length))
    patterns.append(pattern)
S_length = 2000000  # Close to the limit
S = ''.join(random.choices(patterns, k=S_length // 10))
inputs = []
inputs.append(str(n))
inputs.extend(patterns)
inputs.append(S)
```

Figure 1: An example of our benchmark. It consists of two tasks: generation of valid test case generators and generation of targeted test case generators. To enhance clarity, the example has been presented in a simplified format. For the full example, please refer to Appendix A.

The Canonical Problem Set. The Canonical Problem Set includes various algorithms and data structures implementation tasks. The tasks presented by these problems often involve the canonical implementation of target algorithms or data structures. They feature concise and clear problem statements, typically serving as the first exercise for human coders learning a particular algorithm or data structure. Following the common practice within the competitive programming community, we

select all canonical problems on a third-party online judge (OJ) platform, Luogu[1], to serve as our initial problem set.

All selected problems are publicly licensed to ensure compliance with research ethics.

Since the focus of this work is test case generation, we want to first ensure that the LLMs can properly understand the problems. From the complete pool of NOIP and canonical problems, we first test with OpenAI o1-mini [OpenAI, 2024a], only keeping the problems that o1-mini could fully pass at 1 attempt on Luogu. We then manually select those with clearly defined problem descriptions, data constraints, and a sufficient number of human-written codes. As a result, our final dataset consists of 129 NOIP problems and 79 canonical problems.

2.2 Collection of Human-Written Code

To build our benchmark, we require two types of code for evaluation.

First, we need the correct reference solver programs. These programs are essential for validating the correctness of a test case generator, because fully determining a generator's validity through human expertise is difficult and time-consuming. Instead, we can utilize correct programs to perform a more effective verification by comparing the consistency of their outputs for valid inputs. We collect programs that successfully pass all test cases on Luogu for all problems in our problem set, which we refer to as **standard solver programs**. We manually filter them, retaining only C++ code for subsequent evaluation and ensuring that each problem has more than 5 standard solver programs.

Furthermore, we also need to evaluate the ability of LLMs to understand and reason about errors inherent in code and generate a targeted test case generator. For this purpose, we collect code submissions that fail to pass all test cases on the OJ, which we refer to as **erroneous programs**. We further categorize and analyze these 'errors' in more detail: In terms of evaluation results on the test case from the OJ platform, the results for these programs may correspond to one or more categories listed in Table 1. To facilitate evaluation and ensure the code is related to the problem (otherwise the language model may confused on finding errors), we choose 5 erroneous programs that only pass the online judge test cases at a ratio in the range [0.6,1), and their errors consist solely of one or more from $\{\texttt{WA}, \texttt{TLE}, \texttt{RE}\}$.

Table 1: Possible judge results.

Judge Results	
Result	Description
AC	Accepted, the solver program is correct.
WA	Wrong Answer, the output of the solver program differs from the expected output.
TLE	Time Limit Exceeded, the solver program took more time than allowed.
RE	Runtime Error, the solver program encountered an error during execution.
MLE	Memory Limit Exceeded, the solver program used more memory than allowed.
CE	Compilation Error, the solver program failed to compile.

2.3 Target Instruction Dataset

Finally, to systematically evaluate the capability of language models to generate targeted test case generators given erroneous programs and their errors (a detailed definition will be provided subsequently), we curate a subset of 66 erroneous programs from the dataset corresponding to the NOIP problem set. For each program in this subset, we meticulously annotate its error analysis, instructions for generating a targeted generator, and an example targeted generator. This dataset can be applied for model fine-tuning, in an effort to enhance the model's ability to generate targeted generators. Detailed examples are provided in Appendix C.

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[1]https://www.luogu.com.cn/

3 Evaluating LLM's Ability in Generating Test Case Generators

3.1 Terminologies and Notations

In this section, we introduce the terminologies used in the construction of our benchmark.

In our benchmark, we denote a programming problem as a pair (π, C), where π is the problem statement, and C represents a test case set (i.e., test suite in software engineering). The problem statement π specifies the test case constraints for all variables within the test case input. Each test case $c_i = (\tau_i, \phi_i)$ contains a valid input τ_i as well as an expected output ϕ_i.

In the context of real-world algorithmic competitions, there might be multiple valid correct outputs for an input; however, for simplicity in evaluation, we will only consider problems where there is only one correct answer for any given test case input. Typically, the problem statement π in CP problems specifies the variable constraints for all variables within the test case input[2].

A test case input generator Γ is a program that generates random or deterministic test case inputs. In our benchmark, all generators are implemented in Python.

A solver program Σ is a program that attempts to solve a given problem. It can be executed with a test case input and return an output. An automatic judge $J : (\tau, \phi, \Sigma) \to \omega$ can run a solver program, and return a judge result $\omega \in \{\texttt{AC}, \texttt{WA}, \texttt{TLE}, \texttt{RE}\}$ concerning the test case τ. Building upon this, we define a solver program as a **standard solver program** Σ_{std} if it executes successfully and produces the expected output within a reasonable time for all test case inputs that satisfy the constraints. Correspondingly, a solver program is defined as a **erroneous solver program** Σ_{err} if there exists at least one valid test case for which the program either fails to executes successfully or does not produce the expected output. This definition can be formalized as follows:

$$\forall (\tau, \phi) \in T, \ J(\tau, \phi, \Sigma_{\text{std}}) = \texttt{AC}, \tag{1}$$

$$\exists (\tau_e, \phi_e) \in T, \ J(\tau_e, \phi_e, \Sigma_{\text{err}}) \in \{\texttt{WA}, \texttt{RE}, \texttt{TLE}\}. \tag{2}$$

3.2 Task: The Generation of Valid Test Case Generators

Now we formalize our main task: LLM generation of a test case generator.

In this work, the prompt received by the LLM consists of the problem statement π and the task instructions Θ. The expected response is a test case generator Γ.

In this task, given a prompt, we have the language model generate n samples of generators. For the generator Γ_i, we run it m times to get m test cases, and form these m test cases as a new test case input set T_i^{in}. We evaluate the test case input set in two different ways and get a metric r.

Our first goal is to evaluate the model's ability to generate valid generators given a CP problem. In this task, the prompt to LLMs includes the problem statement and an instruction prompt. The LLM is instructed to generate a valid generator adhering to a specified format, referencing the problem statement and variable constraints. It also includes a Chain-of-Thought [Wei et al., 2022] prompt and a one-shot demonstration of a (π, Γ) pair. In addition, we also manually fix the values of certain variables based on the problem description. They are mainly in the statements expressing the data ranges of quantities in the problem. We choose the largest possible value as the constraint. For example, a statement 'Alice has $n \leq 10^5$ apples' indicates we have a constraint that $n = 10^5$.

The LLMs are required to set these variables to our specified values in their generators. The main purpose of this requirement is to prevent the LLM from "cheating" by generating generators with a tiny test case range, which could make the task trivial. We perform independent sampling from LLMs $n = 10$ times, uniformly setting the temperature to 1 to get 10 generator samples.

For each generator, we evaluate its validity by the standard solver programs. Specifically, we run the generator $m = 10$ times to generate m test cases. These test cases are then provided to at least 5 standard solver programs associated with the problem. For a given test case τ, it is valid if all solver

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[2]For example, a problem statement might include the following description: "For all test cases, $1 \leq m \leq 10^5$." It provides a variable constraint of m in natural language.

programs produce the same output and none of them crash or exceed the time limit of 10 wall-clock seconds.

We define r_i^π as an indicator variable, namely if generator Γ_i is valid for problem π, $r_i = 1$, otherwise $r_i = 0$. The final metric r^π is denoted as valid@k, which is formalized analogous to the popular pass@k metric, i.e.,

$$r^\pi = 1 - \frac{\binom{n-c}{k}}{\binom{n}{k}},\qquad(3)$$

where $c = \sum_{i=1}^{n}[r_i = 1]$.

3.3 Evaluating Generation of Targeted Generators

Our second goal is to evaluate the model's ability to generate targeted generators for specified erroneous solver programs. In this task, the instruction prompt is followed by an erroneous solver program Σ_{err}. The LLM is instructed to generate a targeted generator, which can generate a test case to expose flaws of that program, leading it to produce a wrong output, crash, or exceed the time limit. As an intermediate step, we also instruct the language model to explicitly output a reasoning process that covers code issues and instructions for writing the corresponding targeted generator. This serves as a form of Chain-of-Thought prompting. We also give a one-shot demonstration of a $(\pi, \Sigma_{\text{err}}, \Gamma)$ triplet.

Consistent with the first task, we perform independent sampling from LLMs $n = 10$ times, uniformly setting the temperature to 1 for each sample. For each generator Γ_i, our requirements in this task are stricter. Specifically, for each $(\pi, \Sigma_{\text{err}})$ pair, the generator generates a single test case τ $(m = 1)$. This test case is then submitted both to a selected standard solver program (Σ_{std}) and the erroneous program (Σ_{err}). A targeted generator Γ_i is considered successful if Σ_{std} executes successfully, and the output of Σ_{err} differs from that of Σ_{std}, or Σ_{err} crashes or exceeds the time limit.

Similar to the first task, we define r_i as an indicator variable, and the final metric $r^{(\pi, \Sigma_{\text{err}})}$ is denoted as success@k, formulated as:

$$r^{(\pi, \Sigma_{\text{err}})} = 1 - \frac{\binom{n-c}{k}}{\binom{n}{k}},\qquad(4)$$

where $c = \sum_{i=1}^{n}[r_i = 1]$. In our benchmark, for each problem, we choose 5 corresponding erroneous solver programs.

3.4 Human Performance as a Reference

To better evaluate the performance of the language model on our task, we also collect data on human performance, serving as a reference.

6 experienced volunteers (all of them are undergraduate students with competitive programming experience of at least 3 years) are recruited to complete the two tasks stated above. For the first task, human experts are each assigned a total of 25-40 problems, with the requirement to produce a valid generator for each within a 15-minute time limit. For the second task, experts are each assigned a total of 50-80 erroneous solver programs, derived from the same 25-40 problems (with at least two erroneous programs per problem). For both tasks, failure is recorded if a generator is not successfully produced within this time constraint.

4 Experimental Results

4.1 Valid Test Case Generator Generation

In this section, we investigate our first research question regarding the model's ability to generate valid test case generators. We perform experiments on multiple state-of-the-art language models,
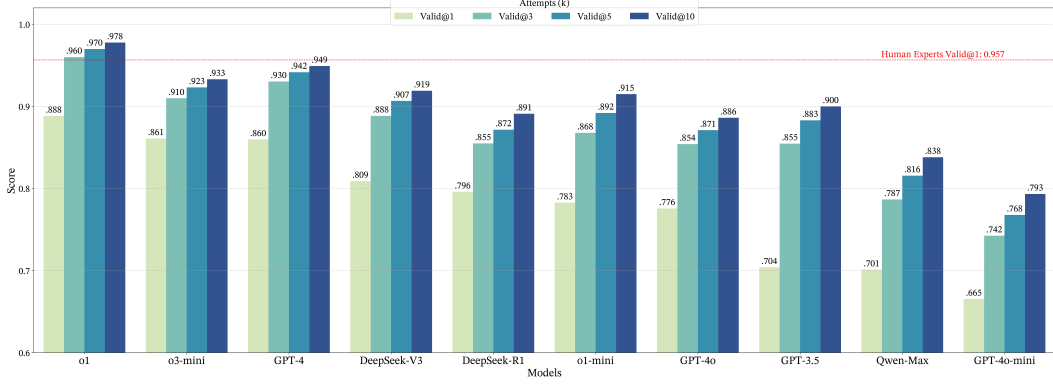
Figure 2: Valid@k results. When $k \geq 5$, o1 demonstrated capabilities exceed human level. However, at $k = 1$, the capabilities of most models still fall short of human level.
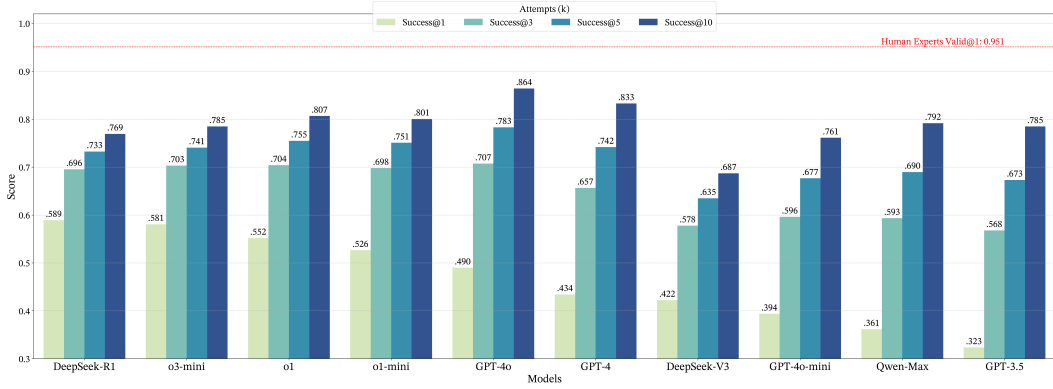

Figure 3: Success@k results. Most models have a poor performance at success@1. However, when the number of samples increases, success@k shows a significant improvement. This suggests that a decent level of ability to generate targeted generators, but requires multiple tries.

including o3-mini [OpenAI, 2025], o1 [OpenAI et al., 2024a], GPT-4 [OpenAI et al., 2024b], GPT-4o series [OpenAI et al., 2024c, OpenAI, 2024b], Deepseek V3 [DeepSeek-AI et al., 2025], Qwen-Max [Qwen et al., 2025]. We find that, for this task, all models' performances on the two datasets are similar. Therefore, we present the results of the combined dataset, depicted in Figure 2. The full results are detailed in Appendix D.

As illustrated, the majority of models exhibit relatively strong performance on this task, especially with a greater number of attempts. Advanced reasoning models, such as o1, perform better. However, it is important to note that if the model fails to achieve a high valid@1 in this task (valid@1 of most models are above 0.7), this has certain implications for real-world scenarios, as in practical competitions, one invalid test case could potentially require significant costs for re-judging.

4.2 Targeted Test Case Generator Generation

Next, we present the results of our study on the targeted test case generator task. For ease of presentation, we similarly show the results from the combined dataset, as illustrated in Figure 3. The full results are also available in Appendix D.

We find that most models exhibit poor performance on the success@1 metric (success@1 of most models is below 0.6). Even state-of-the-art models show a significant capability gap compared to human experts. This disparity indicates that the models' ability to understand program errors is still quite limited.

Furthermore, it is worth noting that, in our dataset, many errors in the erroneous programs are relatively straightforward but involve specific details of the problem statement. Human experts can
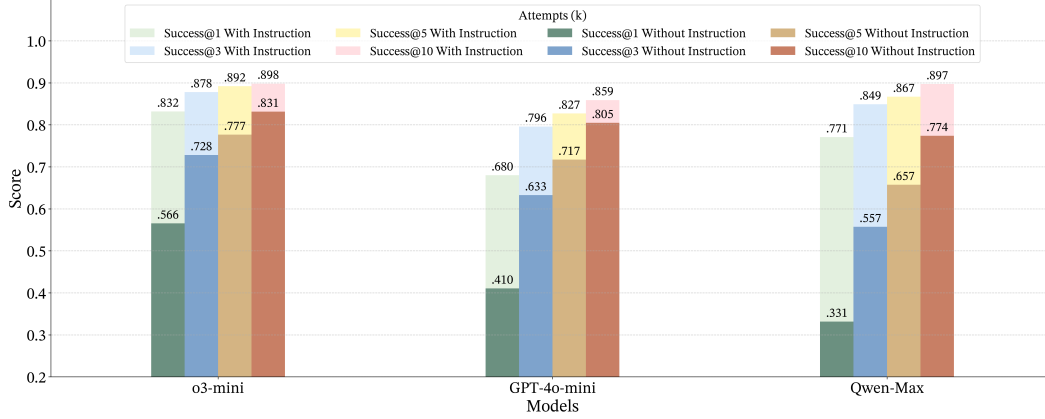
Figure 4: Success@k in Targeted Instruction Dataset. With the help of the target instructions, all 3 models show a significant improvement in success@1.

solve these types of issues with ease, yet LLM fails to produce the correct targeted generator. We provide an example illustrating this situation in Figure 1, and more examples in Appendix A.

From this evaluation result, we believe that addressing how to enable models to understand code-level details (as opposed to summarizing functionality, at which models are good) and identify the corresponding errors is a problem worthy of significant attention and future research.

4.3 Curated Instructions Help LLMs Generate Targeted Generators Better

Finally, we analyze the impact of targeted instructions on model performance. First, we examine the application of our targeted instruction dataset as contextual information for advanced closed-source models. For each pair of problem and erroneous program(s) $(\pi, \Sigma_{\text{err}})$, we incorporate the target instruction (refer to Figure 1) associated with Σ_{err} into the prompt, directing the language model to generate targeted generators based on the provided instruction. We select three representative models to illustrate our experimental findings, which are presented in Figure 4. Comprehensive experimental results are detailed in Appendix D.

We observe that the presence of instructions leads to a significant improvement in the model's success@1 score. This suggests that our target instructions are highly beneficial in assisting the model's comprehension of the specific issues within erroneous programs. However, it is observed that the model could not generate targeted generators for all erroneous solver programs even after 10 sampling attempts, indicating that its performance on this task is constrained by its inherent capabilities.

On the other hand, we perform supervised fine-tuning (SFT) of the 14B variant of Qwen2.5 instruct model on the target instruction dataset using Low-Rank Adaptation (LoRA) [Hu et al., 2021]. The model was optimized using paged AdamW 8bit [Loshchilov and Hutter, 2019] with a learning rate of 2×10^{-4}, weight decay of 0.01, and linear learning rate scheduling, trained for 100 epochs. All training samples were formatted with the Alpaca-style [Taori et al., 2023] instruction templates. We do experiments on the Canonical Problem Set, which are presented in Figure 5. Through a case study (detailed in Appendix A), we reveal that the base model exhibits severe hallucination. However, after fine-tuning, the model's output was effectively constrained to the correct format. We also find that the finetuned model tends to over-identify common issues in the given erroneous code snippets. This manifests in two key patterns:

Over-sensitivity to common mistakes. The finetuned model frequently flags integer overflow or array out-of-bounds issues in the code snippets, even when safeguards exist.

Misestimates time complexity. The finetuned model sometimes misestimates algorithmic time complexity, regardless of the given data range.
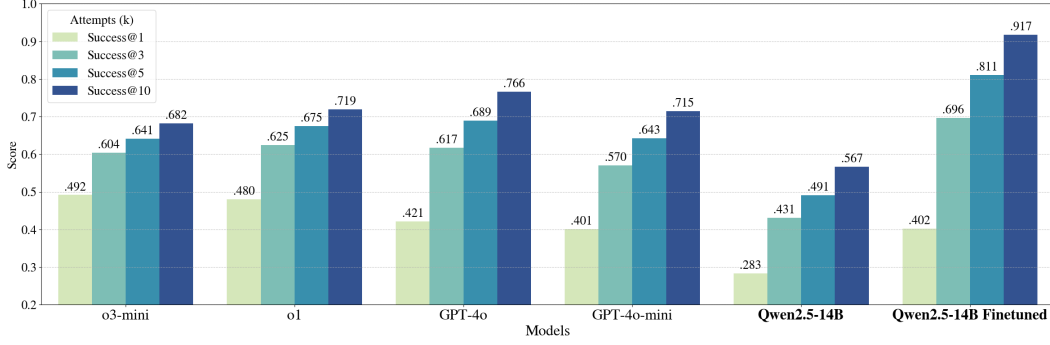
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Figure 5: Success@k in the Canonical Problem Dataset. The last two groups show the results before and after fine-tuning Qwen2.5-14B. It can be observed that the fine-tuned Qwen2.5-14B achieves capabilities close to GPT-4o-mini.

This might imply that the model can learn knowledge from the dataset, but due to its own capability, the improvement may be limited.

5 Related Work

5.1 LLM for Code Generation

Large Language Models (LLMs) have demonstrated remarkable capabilities in code generation. The success of prompt engineering techniques such as Chain-of-Thought [Wei et al., 2022] has been verified in numerous fields, including code generation. Structured Chain-of-Thought [Li et al., 2023] explicitly incorporates programming structures (sequence, branch, and loop) into the reasoning process, guiding LLMs to think systematically about code design before implementation. ClarifyGPT [Mu et al., 2024] introduces an interactive clarification mechanism that detects ambiguous requirements through code consistency checks, generates targeted clarifying questions, and refines requirements before final code generation.

Self-Debugging teaches LLMs to perform rubber duck debugging without external feedback, where models identify mistakes by explaining generated code line-by-line or tracing execution. LDB [Zhong et al., 2024] segments programs into basic blocks and tracks intermediate variable values during runtime execution, enabling LLMs to verify correctness against task descriptions block by block. SelfEvolve [Jiang et al., 2023] implements a two-step pipeline where LLMs extract knowledge from input prompts to generate intermediate code, then act as expert programmers to debug based on interpreter feedback without requiring special test cases. Reflexion [Shinn et al., 2023] learns through verbal feedback and self-reflection, with an agent explicitly critiquing each response based on external data, generating citations, and enumerating missing aspects of the response.

5.2 LLM Capabilities on Competition-Level Programming Problems

Beyond standard software development, competitive programming represents another significant domain for code generation tasks, yielding a vast and diverse collection of code snippets and programs. Competition-level problems are characterized by their high reasoning complexity and the demand for precise algorithmic implementation, thereby constituting a highly integrative reasoning challenge.

AlphaCode [Li et al., 2022b] was the first to introduce a pipeline for generating code in the context of competitive programming. Although Large Language Models (LLMs) have demonstrated proficiency in generating code for general tasks, the challenge becomes more significant when applied to this domain. The ability of LLMs to generate human-level solutions in such contexts has sparked discussions about their potential as general problem solvers. However, findings from the USACO benchmark [Shi et al., 2024] highlight the substantial challenges that LLMs currently face. This benchmark, featuring 307 problems from the USA Computing Olympiad that require complex algorithmic reasoning and puzzle-solving skills, reveals that GPT-4 [OpenAI et al., 2024b] achieves only 8.7% pass@1 accuracy with zero-shot prompting. Even when augmented with methods like self-

reflection and episodic retrieval, the model's accuracy improves to only 20.2%, indicating persistent difficulty in comprehensively solving the benchmark.

Nevertheless, with the advancement of large reasoning models, their performance on competition-level programming problems has been continuously improving. For instance, OpenAI et al. [2025] systematically investigated the capabilities of these models in solving highly challenging competition-level programming problems. Concurrently, Quan et al. [2025] has benchmarked the performance of various language models within a general, human-comparable setting.

6 Conclusion

This work underscores the critical importance of equipping large language models with the capability to verify code correctness, particularly through the generation of reliable test cases. While LLMs have shown impressive strides in code generation, the equally vital task of verifying their output and that of human-written code remains a significant challenge. Our investigation, grounded in the context of competitive programming, revealed limitations in existing evaluation methodologies concerning the systematic assessment and analysis of LLM-generated test case generators. Furthermore, open questions persist regarding the extent of LLMs' true reasoning abilities versus mere memorization and their genuine comprehension of code semantics.

To address these gaps and provide a rigorous framework for evaluation, we introduce TCGBench, a novel benchmark specifically designed for assessing the capability of LLMs to generate test case generators. Our contributions include the curation of a comprehensive dataset of competitive programming problems, standard and erroneous solutions, and the definition of two key evaluation tasks focusing on the generation of valid and targeted test case generators. Crucially, we develop a high-quality dataset for code analysis, demonstrating its utility in enhancing LLM performance through prompting and fine-tuning for generating targeted test cases. TCGBench thus provides a foundational platform for future research to systematically probe and advance LLM capabilities in code verification via robust test case generation.

7 Limitations

This work is subject to several limitations. 1) Due to the scarcity of competition-level programming (CP) problems, this research utilized a subset of problems with extensive human verification as the dataset to facilitate the investigation; consequently, the difficulty and diversity of the data are restricted. 2) This work focuses on CP problems, while demanding significant reasoning, meaning its findings may not directly translate to software engineering contexts, where code structures differ considerably; establishing a robust benchmark in long-form software engineering scenarios might more accurately reflect real-world development requirements. 3) While this work focuses on building a reliable benchmark for evaluating LLMs in test case generation, it does not explore ways to improve model performance. For example, whether models can improve without human-written target instructions—perhaps via reinforcement learning—remains an open question.

References

Yujia Li, David Choi, Junyoung Chung, Nate Kushman, Julian Schrittwieser, Rémi Leblond, Tom Eccles, James Keeling, Felix Gimeno, Agustin Dal Lago, Thomas Hubert, Peter Choy, Cyprien de Masson d'Autume, Igor Babuschkin, Xinyun Chen, Po-Sen Huang, Johannes Welbl, Sven Gowal, Alexey Cherepanov, James Molloy, Daniel J. Mankowitz, Esme Sutherland Robson, Pushmeet Kohli, Nando de Freitas, Koray Kavukcuoglu, and Oriol Vinyals. Competition-level code generation with alphacode. *Science*, 378(6624):1092–1097, 2022a. doi: 10.1126/science.abq1158. URL https://www.science.org/doi/abs/10.1126/science.abq1158.

Juyong Jiang, Fan Wang, Jiasi Shen, Sungju Kim, and Sunghun Kim. A survey on large language models for code generation, 2024. URL https://arxiv.org/abs/2406.00515.

Naman Jain, King Han, Alex Gu, Wen-Ding Li, Fanjia Yan, Tianjun Zhang, Sida Wang, Armando Solar-Lezama, Koushik Sen, and Ion Stoica. Livecodebench: Holistic and contamination free evaluation of large language models for code. In *The Thirteenth International Conference on Learning Representations*, 2025. URL https://openreview.net/forum?id=chfJJYC3iL.

DeepSeek-AI, Aixin Liu, Bei Feng, Bing Xue, Bingxuan Wang, Bochao Wu, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, Damai Dai, Daya Guo, Dejian Yang, Deli Chen, Dongjie Ji, Erhang Li, Fangyun Lin, Fucong Dai, Fuli Luo, Guangbo Hao, Guanting Chen, Guowei Li, H. Zhang, Han Bao, Hanwei Xu, Haocheng Wang, Haowei Zhang, Honghui Ding, Huajian Xin, Huazuo Gao, Hui Li, Hui Qu, J. L. Cai, Jian Liang, Jianzhong Guo, Jiaqi Ni, Jiashi Li, Jiawei Wang, Jin Chen, Jingchang Chen, Jingyang Yuan, Junjie Qiu, Junlong Li, Junxiao Song, Kai Dong, Kai Hu, Kaige Gao, Kang Guan, Kexin Huang, Kuai Yu, Lean Wang, Lecong Zhang, Lei Xu, Leyi Xia, Liang Zhao, Litong Wang, Liyue Zhang, Meng Li, Miaojun Wang, Mingchuan Zhang, Minghua Zhang, Minghui Tang, Mingming Li, Ning Tian, Panpan Huang, Peiyi Wang, Peng Zhang, Qiancheng Wang, Qihao Zhu, Qinyu Chen, Qiushi Du, R. J. Chen, R. L. Jin, Ruiqi Ge, Ruisong Zhang, Ruizhe Pan, Runji Wang, Runxin Xu, Ruoyu Zhang, Ruyi Chen, S. S. Li, Shanghao Lu, Shangyan Zhou, Shanhuang Chen, Shaoqing Wu, Shengfeng Ye, Shengfeng Ye, Shirong Ma, Shiyu Wang, Shuang Zhou, Shuiping Yu, Shunfeng Zhou, Shuting Pan, T. Wang, Tao Yun, Tian Pei, Tianyu Sun, W. L. Xiao, Wangding Zeng, Wanjia Zhao, Wei An, Wen Liu, Wenfeng Liang, Wenjun Gao, Wenqin Yu, Wentao Zhang, X. Q. Li, Xiangyue Jin, Xianzu Wang, Xiao Bi, Xiaodong Liu, Xiaohan Wang, Xiaojin Shen, Xiaokang Chen, Xiaokang Zhang, Xiaosha Chen, Xiaotao Nie, Xiaowen Sun, Xiaoxiang Wang, Xin Cheng, Xin Liu, Xin Xie, Xingchao Liu, Xingkai Yu, Xinnan Song, Xinxia Shan, Xinyi Zhou, Xinyu Yang, Xinyuan Li, Xuecheng Su, Xuheng Lin, Y. K. Li, Y. Q. Wang, Y. X. Wei, Y. X. Zhu, Yang Zhang, Yanhong Xu, Yanhong Xu, Yanping Huang, Yao Li, Yao Zhao, Yaofeng Sun, Yaohui Li, Yaohui Wang, Yi Yu, Yi Zheng, Yichao Zhang, Yifan Shi, Yiliang Xiong, Ying He, Ying Tang, Yishi Piao, Yisong Wang, Yixuan Tan, Yiyang Ma, Yiyuan Liu, Yongqiang Guo, Yu Wu, Yuan Ou, Yuchen Zhu, Yuduan Wang, Yue Gong, Yuheng Zou, Yujia He, Yukun Zha, Yunfan Xiong, Yunxian Ma, Yuting Yan, Yuxiang Luo, Yuxiang You, Yuxuan Liu, Yuyang Zhou, Z. F. Wu, Z. Z. Ren, Zehui Ren, Zhangli Sha, Zhe Fu, Zhean Xu, Zhen Huang, Zhen Zhang, Zhenda Xie, Zhengyan Zhang, Zhewen Hao, Zhibin Gou, Zhicheng Ma, Zhigang Yan, Zhihong Shao, Zhipeng Xu, Zhiyu Wu, Zhongyu Zhang, Zhuoshu Li, Zihui Gu, Zijia Zhu, Zijun Liu, Zilin Li, Ziwei Xie, Ziyang Song, Ziyi Gao, and Zizheng Pan. Deepseek-v3 technical report, 2025. URL `https://arxiv.org/abs/2412.19437`.

Qwen, :, An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li, Tianyi Tang, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. Qwen2.5 technical report, 2025. URL `https://arxiv.org/abs/2412.15115`.

Kimi Team, Angang Du, Bofei Gao, Bowei Xing, Changjiu Jiang, Cheng Chen, Cheng Li, Chenjun Xiao, Chenzhuang Du, Chonghua Liao, Chuning Tang, Congcong Wang, Dehao Zhang, Enming Yuan, Enzhe Lu, Fengxiang Tang, Flood Sung, Guangda Wei, Guokun Lai, Haiqing Guo, Han Zhu, Hao Ding, Hao Hu, Hao Yang, Hao Zhang, Haotian Yao, Haotian Zhao, Haoyu Lu, Haoze Li, Haozhen Yu, Hongcheng Gao, Huabin Zheng, Huan Yuan, Jia Chen, Jianhang Guo, Jianlin Su, Jianzhou Wang, Jie Zhao, Jin Zhang, Jingyuan Liu, Junjie Yan, Junyan Wu, Lidong Shi, Ling Ye, Longhui Yu, Mengnan Dong, Neo Zhang, Ningchen Ma, Qiwei Pan, Qucheng Gong, Shaowei Liu, Shengling Ma, Shupeng Wei, Sihan Cao, Siying Huang, Tao Jiang, Weihao Gao, Weimin Xiong, Weiran He, Weixiao Huang, Wenhao Wu, Wenyang He, Xianghui Wei, Xianqing Jia, Xingzhe Wu, Xinran Xu, Xinxing Zu, Xinyu Zhou, Xuehai Pan, Y. Charles, Yang Li, Yangyang Hu, Yangyang Liu, Yanru Chen, Yejie Wang, Yibo Liu, Yidao Qin, Yifeng Liu, Ying Yang, Yiping Bao, Yulun Du, Yuxin Wu, Yuzhi Wang, Zaida Zhou, Zhaoji Wang, Zhaowei Li, Zhen Zhu, Zheng Zhang, Zhexu Wang, Zhilin Yang, Zhiqi Huang, Zihao Huang, Ziyao Xu, and Zonghan Yang. Kimi k1.5: Scaling reinforcement learning with llms, 2025. URL `https://arxiv.org/abs/2501.12599`.

Yiming Huang, Zhenghao Lin, Xiao Liu, Yeyun Gong, Shuai Lu, Fangyu Lei, Yaobo Liang, Yelong Shen, Chen Lin, Nan Duan, and Weizhu Chen. Competition-level problems are effective llm evaluators, 2024. URL `https://arxiv.org/abs/2312.02143`.

OpenAI. Openai o1-mini, Sept 2024a. URL `https://openai.com/index/openai-o1-mini-advancing-cost-efficient-reasoning/`.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, brian ichter, Fei Xia, Ed H. Chi, Quoc V Le, and Denny Zhou. Chain of thought prompting elicits reasoning in large language models.

In Alice H. Oh, Alekh Agarwal, Danielle Belgrave, and Kyunghyun Cho, editors, *Advances in Neural Information Processing Systems*, 2022. URL `https://openreview.net/forum?id=_VjQlMeSB_J`.

OpenAI. Openai o3-mini, Jan 2025. URL `https://openai.com/index/openai-o3-mini/`.

OpenAI, :, Aaron Jaech, Adam Kalai, Adam Lerer, Adam Richardson, Ahmed El-Kishky, Aiden Low, Alec Helyar, Aleksander Madry, Alex Beutel, Alex Carney, Alex Iftimie, Alex Karpenko, Alex Tachard Passos, Alexander Neitz, Alexander Prokofiev, Alexander Wei, Allison Tam, Ally Bennett, Ananya Kumar, Andre Saraiva, Andrea Vallone, Andrew Duberstein, Andrew Kondrich, Andrey Mishchenko, Andy Applebaum, Angela Jiang, Ashvin Nair, Barret Zoph, Behrooz Ghorbani, Ben Rossen, Benjamin Sokolowsky, Boaz Barak, Bob McGrew, Borys Minaiev, Botao Hao, Bowen Baker, Brandon Houghton, Brandon McKinzie, Brydon Eastman, Camillo Lugaresi, Cary Bassin, Cary Hudson, Chak Ming Li, Charles de Bourcy, Chelsea Voss, Chen Shen, Chong Zhang, Chris Koch, Chris Orsinger, Christopher Hesse, Claudia Fischer, Clive Chan, Dan Roberts, Daniel Kappler, Daniel Levy, Daniel Selsam, David Dohan, David Farhi, David Mely, David Robinson, Dimitris Tsipras, Doug Li, Dragos Oprica, Eben Freeman, Eddie Zhang, Edmund Wong, Elizabeth Proehl, Enoch Cheung, Eric Mitchell, Eric Wallace, Erik Ritter, Evan Mays, Fan Wang, Felipe Petroski Such, Filippo Raso, Florencia Leoni, Foivos Tsimpourlas, Francis Song, Fred von Lohmann, Freddie Sulit, Geoff Salmon, Giambattista Parascandolo, Gildas Chabot, Grace Zhao, Greg Brockman, Guillaume Leclerc, Hadi Salman, Haiming Bao, Hao Sheng, Hart Andrin, Hessam Bagherinezhad, Hongyu Ren, Hunter Lightman, Hyung Won Chung, Ian Kivlichan, Ian O'Connell, Ian Osband, Ignasi Clavera Gilaberte, Ilge Akkaya, Ilya Kostrikov, Ilya Sutskever, Irina Kofman, Jakub Pachocki, James Lennon, Jason Wei, Jean Harb, Jerry Twore, Jiacheng Feng, Jiahui Yu, Jiayi Weng, Jie Tang, Jieqi Yu, Joaquin Quiñonero Candela, Joe Palermo, Joel Parish, Johannes Heidecke, John Hallman, John Rizzo, Jonathan Gordon, Jonathan Uesato, Jonathan Ward, Joost Huizinga, Julie Wang, Kai Chen, Kai Xiao, Karan Singhal, Karina Nguyen, Karl Cobbe, Katy Shi, Kayla Wood, Kendra Rimbach, Keren Gu-Lemberg, Kevin Liu, Kevin Lu, Kevin Stone, Kevin Yu, Lama Ahmad, Lauren Yang, Leo Liu, Leon Maksin, Leyton Ho, Liam Fedus, Lilian Weng, Linden Li, Lindsay McCallum, Lindsey Held, Lorenz Kuhn, Lukas Kondraciuk, Lukasz Kaiser, Luke Metz, Madelaine Boyd, Maja Trebacz, Manas Joglekar, Mark Chen, Marko Tintor, Mason Meyer, Matt Jones, Matt Kaufer, Max Schwarzer, Meghan Shah, Mehmet Yatbaz, Melody Y. Guan, Mengyuan Xu, Mengyuan Yan, Mia Glaese, Mianna Chen, Michael Lampe, Michael Malek, Michele Wang, Michelle Fradin, Mike McClay, Mikhail Pavlov, Miles Wang, Mingxuan Wang, Mira Murati, Mo Bavarian, Mostafa Rohaninejad, Nat McAleese, Neil Chowdhury, Neil Chowdhury, Nick Ryder, Nikolas Tezak, Noam Brown, Ofir Nachum, Oleg Boiko, Oleg Murk, Olivia Watkins, Patrick Chao, Paul Ashbourne, Pavel Izmailov, Peter Zhokhov, Rachel Dias, Rahul Arora, Randall Lin, Rapha Gontijo Lopes, Raz Gaon, Reah Miyara, Reimar Leike, Renny Hwang, Rhythm Garg, Robin Brown, Roshan James, Rui Shu, Ryan Cheu, Ryan Greene, Saachi Jain, Sam Altman, Sam Toizer, Sam Toyer, Samuel Miserendino, Sandhini Agarwal, Santiago Hernandez, Sasha Baker, Scott McKinney, Scottie Yan, Shengjia Zhao, Shengli Hu, Shibani Santurkar, Shraman Ray Chaudhuri, Shuyuan Zhang, Siyuan Fu, Spencer Papay, Steph Lin, Suchir Balaji, Suvansh Sanjeev, Szymon Sidor, Tal Broda, Aidan Clark, Tao Wang, Taylor Gordon, Ted Sanders, Tejal Patwardhan, Thibault Sottiaux, Thomas Degry, Thomas Dimson, Tianhao Zheng, Timur Garipov, Tom Stasi, Trapit Bansal, Trevor Creech, Troy Peterson, Tyna Eloundou, Valerie Qi, Vineet Kosaraju, Vinnie Monaco, Vitchyr Pong, Vlad Fomenko, Weiyi Zheng, Wenda Zhou, Wes McCabe, Wojciech Zaremba, Yann Dubois, Yinghai Lu, Yining Chen, Young Cha, Yu Bai, Yuchen He, Yuchen Zhang, Yunyun Wang, Zheng Shao, and Zhuohan Li. Openai o1 system card, 2024a. URL `https://arxiv.org/abs/2412.16720`.

OpenAI, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mohammad Bavarian, Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty

Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Jan Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O'Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr H. Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine B. Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, CJ Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. Gpt-4 technical report, 2024b. URL https://arxiv.org/abs/2303.08774.

OpenAI, :, Aaron Hurst, Adam Lerer, Adam P. Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, Alec Radford, Aleksander Mądry, Alex Baker-Whitcomb, Alex Beutel, Alex Borzunov, Alex Carney, Alex Chow, Alex Kirillov, Alex Nichol, Alex Paino, Alex Renzin, Alex Tachard Passos, Alexander Kirillov, Alexi Christakis, Alexis Conneau, Ali Kamali, Allan Jabri, Allison Moyer, Allison Tam, Amadou Crookes, Amin Tootoochian, Amin Tootoonchian, Ananya Kumar, Andrea Vallone, Andrej Karpathy, Andrew Braunstein, Andrew Cann, Andrew Codispoti, Andrew Galu, Andrew Kondrich, Andrew Tulloch, Andrey Mishchenko, Angela Baek, Angela Jiang, Antoine Pelisse, Antonia Woodford, Anuj Gosalia, Arka Dhar, Ashley Pantuliano, Avi Nayak, Avital Oliver, Barret Zoph, Behrooz Ghorbani, Ben Leimberger, Ben Rossen, Ben Sokolowsky, Ben Wang, Benjamin Zweig, Beth Hoover, Blake Samic, Bob McGrew, Bobby Spero, Bogo Giertler, Bowen Cheng, Brad Lightcap, Brandon Walkin, Brendan Quinn, Brian Guarraci, Brian Hsu, Bright Kellogg, Brydon Eastman, Camillo Lugaresi, Carroll Wainwright, Cary Bassin, Cary Hudson, Casey Chu, Chad Nelson, Chak Li, Chan Jun Shern, Channing Conger, Charlotte Barette, Chelsea Voss, Chen Ding, Cheng Lu, Chong Zhang, Chris Beaumont, Chris Hallacy, Chris Koch, Christian Gibson, Christina Kim, Christine Choi, Christine McLeavey, Christopher Hesse, Claudia Fischer, Clemens Winter, Coley Czarnecki, Colin Jarvis, Colin Wei, Constantin Koumouzelis, Dane Sherburn, Daniel Kappler, Daniel Levin, Daniel Levy, David Carr, David Farhi, David Mely, David Robinson, David Sasaki, Denny Jin, Dev Valladares, Dimitris Tsipras, Doug Li, Duc Phong Nguyen, Duncan Findlay, Edede Oiwoh, Edmund Wong, Ehsan Asdar, Elizabeth Proehl, Elizabeth Yang, Eric Antonow, Eric Kramer, Eric Peterson, Eric Sigler, Eric Wallace, Eugene Brevdo, Evan Mays, Farzad Khorasani,

Felipe Petroski Such, Filippo Raso, Francis Zhang, Fred von Lohmann, Freddie Sulit, Gabriel Goh, Gene Oden, Geoff Salmon, Giulio Starace, Greg Brockman, Hadi Salman, Haiming Bao, Haitang Hu, Hannah Wong, Haoyu Wang, Heather Schmidt, Heather Whitney, Heewoo Jun, Hendrik Kirchner, Henrique Ponde de Oliveira Pinto, Hongyu Ren, Huiwen Chang, Hyung Won Chung, Ian Kivlichan, Ian O'Connell, Ian O'Connell, Ian Osband, Ian Silber, Ian Sohl, Ibrahim Okuyucu, Ikai Lan, Ilya Kostrikov, Ilya Sutskever, Ingmar Kanitscheider, Ishaan Gulrajani, Jacob Coxon, Jacob Menick, Jakub Pachocki, James Aung, James Betker, James Crooks, James Lennon, Jamie Kiros, Jan Leike, Jane Park, Jason Kwon, Jason Phang, Jason Teplitz, Jason Wei, Jason Wolfe, Jay Chen, Jeff Harris, Jenia Varavva, Jessica Gan Lee, Jessica Shieh, Ji Lin, Jiahui Yu, Jiayi Weng, Jie Tang, Jieqi Yu, Joanne Jang, Joaquin Quinonero Candela, Joe Beutler, Joe Landers, Joel Parish, Johannes Heidecke, John Schulman, Jonathan Lachman, Jonathan McKay, Jonathan Uesato, Jonathan Ward, Jong Wook Kim, Joost Huizinga, Jordan Sitkin, Jos Kraaijeveld, Josh Gross, Josh Kaplan, Josh Snyder, Joshua Achiam, Joy Jiao, Joyce Lee, Juntang Zhuang, Justyn Harriman, Kai Fricke, Kai Hayashi, Karan Singhal, Katy Shi, Kavin Karthik, Kayla Wood, Kendra Rimbach, Kenny Hsu, Kenny Nguyen, Keren Gu-Lemberg, Kevin Button, Kevin Liu, Kiel Howe, Krithika Muthukumar, Kyle Luther, Lama Ahmad, Larry Kai, Lauren Itow, Lauren Workman, Leher Pathak, Leo Chen, Li Jing, Lia Guy, Liam Fedus, Liang Zhou, Lien Mamitsuka, Lilian Weng, Lindsay McCallum, Lindsey Held, Long Ouyang, Louis Feuvrier, Lu Zhang, Lukas Kondraciuk, Lukasz Kaiser, Luke Hewitt, Luke Metz, Lyric Doshi, Mada Aflak, Maddie Simens, Madelaine Boyd, Madeleine Thompson, Marat Dukhan, Mark Chen, Mark Gray, Mark Hudnall, Marvin Zhang, Marwan Aljubeh, Mateusz Litwin, Matthew Zeng, Max Johnson, Maya Shetty, Mayank Gupta, Meghan Shah, Mehmet Yatbaz, Meng Jia Yang, Mengchao Zhong, Mia Glaese, Mianna Chen, Michael Janner, Michael Lampe, Michael Petrov, Michael Wu, Michele Wang, Michelle Fradin, Michelle Pokrass, Miguel Castro, Miguel Oom Temudo de Castro, Mikhail Pavlov, Miles Brundage, Miles Wang, Minal Khan, Mira Murati, Mo Bavarian, Molly Lin, Murat Yesildal, Nacho Soto, Natalia Gimelshein, Natalie Cone, Natalie Staudacher, Natalie Summers, Natan LaFontaine, Neil Chowdhury, Nick Ryder, Nick Stathas, Nick Turley, Nik Tezak, Niko Felix, Nithanth Kudige, Nitish Keskar, Noah Deutsch, Noel Bundick, Nora Puckett, Ofir Nachum, Ola Okelola, Oleg Boiko, Oleg Murk, Oliver Jaffe, Olivia Watkins, Olivier Godement, Owen Campbell-Moore, Patrick Chao, Paul McMillan, Pavel Belov, Peng Su, Peter Bak, Peter Bakkum, Peter Deng, Peter Dolan, Peter Hoeschele, Peter Welinder, Phil Tillet, Philip Pronin, Philippe Tillet, Prafulla Dhariwal, Qiming Yuan, Rachel Dias, Rachel Lim, Rahul Arora, Rajan Troll, Randall Lin, Rapha Gontijo Lopes, Raul Puri, Reah Miyara, Reimar Leike, Renaud Gaubert, Reza Zamani, Ricky Wang, Rob Donnelly, Rob Honsby, Rocky Smith, Rohan Sahai, Rohit Ramchandani, Romain Huet, Rory Carmichael, Rowan Zellers, Roy Chen, Ruby Chen, Ruslan Nigmatullin, Ryan Cheu, Saachi Jain, Sam Altman, Sam Schoenholz, Sam Toizer, Samuel Miserendino, Sandhini Agarwal, Sara Culver, Scott Ethersmith, Scott Gray, Sean Grove, Sean Metzger, Shamez Hermani, Shantanu Jain, Shengjia Zhao, Sherwin Wu, Shino Jomoto, Shirong Wu, Shuaiqi, Xia, Sonia Phene, Spencer Papay, Srinivas Narayanan, Steve Coffey, Steve Lee, Stewart Hall, Suchir Balaji, Tal Broda, Tal Stramer, Tao Xu, Tarun Gogineni, Taya Christianson, Ted Sanders, Tejal Patwardhan, Thomas Cunninghman, Thomas Degry, Thomas Dimson, Thomas Raoux, Thomas Shadwell, Tianhao Zheng, Todd Underwood, Todor Markov, Toki Sherbakov, Tom Rubin, Tom Stasi, Tomer Kaftan, Tristan Heywood, Troy Peterson, Tyce Walters, Tyna Eloundou, Valerie Qi, Veit Moeller, Vinnie Monaco, Vishal Kuo, Vlad Fomenko, Wayne Chang, Weiyi Zheng, Wenda Zhou, Wesam Manassra, Will Sheu, Wojciech Zaremba, Yash Patil, Yilei Qian, Yongjik Kim, Youlong Cheng, Yu Zhang, Yuchen He, Yuchen Zhang, Yujia Jin, Yunxing Dai, and Yury Malkov. Gpt-4o system card, 2024c. URL `https://arxiv.org/abs/2410.21276`.

OpenAI. Gpt-4o mini: advancing cost-efficient intelligence, Jul 2024b. URL `https://openai.com/index/gpt-4o-mini-advancing-cost-efficient-intelligence/`.

Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models, 2021. URL `https://arxiv.org/abs/2106.09685`.

Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization, 2019. URL `https://arxiv.org/abs/1711.05101`.

Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Stanford alpaca: An instruction-following llama model. `https://github.com/tatsu-lab/stanford_alpaca`, 2023.

Jia Li, Ge Li, Yongming Li, and Zhi Jin. Structured chain-of-thought prompting for code generation. *ACM Transactions on Software Engineering and Methodology*, 34:1 – 23, 2023. URL `https://api.semanticscholar.org/CorpusID:258615421`.

Fangwen Mu, Lin Shi, Song Wang, Zhuohao Yu, Binquan Zhang, ChenXue Wang, Shichao Liu, and Qing Wang. Clarifygpt: A framework for enhancing llm-based code generation via requirements clarification. *Proc. ACM Softw. Eng.*, 1:2332–2354, 2024. URL `https://api.semanticscholar.org/CorpusID:271170508`.

Li Zhong, Zilong Wang, and Jingbo Shang. Ldb: A large language model debugger via verifying runtime execution step-by-step. *ArXiv*, abs/2402.16906, 2024. URL `https://api.semanticscholar.org/CorpusID:270226918`.

Shuyang Jiang, Yuhao Wang, and Yu Wang. Selfevolve: A code evolution framework via large language models. *ArXiv*, abs/2306.02907, 2023. URL `https://api.semanticscholar.org/CorpusID:259076266`.

Noah Shinn, Federico Cassano, Beck Labash, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. Reflexion: language agents with verbal reinforcement learning. In *Neural Information Processing Systems*, 2023. URL `https://api.semanticscholar.org/CorpusID:258833055`.

Yujia Li, David Choi, Junyoung Chung, Nate Kushman, Julian Schrittwieser, Rémi Leblond, Tom Eccles, James Keeling, Felix Gimeno, Agustin Dal Lago, et al. Competition-level code generation with alphacode. *Science*, 378(6624):1092–1097, 2022b.

Quan Shi, Michael Tang, Karthik Narasimhan, and Shunyu Yao. Can language models solve olympiad programming? *arXiv preprint arXiv:2404.10952*, 2024.

OpenAI, :, Ahmed El-Kishky, Alexander Wei, Andre Saraiva, Borys Minaiev, Daniel Selsam, David Dohan, Francis Song, Hunter Lightman, Ignasi Clavera, Jakub Pachocki, Jerry Tworek, Lorenz Kuhn, Lukasz Kaiser, Mark Chen, Max Schwarzer, Mostafa Rohaninejad, Nat McAleese, o3 contributors, Oleg Mürk, Rhythm Garg, Rui Shu, Szymon Sidor, Vineet Kosaraju, and Wenda Zhou. Competitive programming with large reasoning models, 2025. URL `https://arxiv.org/abs/2502.06807`.

Shanghaoran Quan, Jiaxi Yang, Bowen Yu, Bo Zheng, Dayiheng Liu, An Yang, Xuancheng Ren, Bofei Gao, Yibo Miao, Yunlong Feng, Zekun Wang, Jian Yang, Zeyu Cui, Yang Fan, Yichang Zhang, Binyuan Hui, and Junyang Lin. Codeelo: Benchmarking competition-level code generation of llms with human-comparable elo ratings, 2025. URL `https://arxiv.org/abs/2501.01257`.

A Detailed Examples and Case Studies

In this section, we provide detailed examples from our dataset and conduct case studies.

A.1 Problem Statement

Figure 6 shows an example of a complete problem statement.

Problem Description

A train departs from the starting station (called station 1) with a passengers boarding at this station. The train then arrives at station 2, where people get on and off, but the number of people getting on equals the number getting off. Therefore, when departing from station 2 (i.e., before arriving at station 3), the number of passengers on the train remains a. From station 3 onwards (including station 3), the number of people getting on and off follows a certain pattern: the number of people getting on is the sum of the number of people who got on at the previous two stations, while the number of people getting off equals the number of people who got on at the previous station. This pattern continues until the second-to-last station (station $n - 1$). Given that there are n stations in total, a people board at the starting station, and m people get off at the last station (all passengers disembark), how many passengers are on the train after leaving station x?

Input Format

The input consists of only one line with four integers, representing the number of people boarding at the starting station a, the number of stations n, the number of people getting off at the final station m, and the station number x for which the answer is sought.

Output Format

Output a single line with one integer representing the answer: the number of passengers on the train after leaving station x.

Sample Input

```
5 7 32 4
```

Sample Output

```
13
```

Variable Constraints

For all test cases, it is guaranteed that $1 \le a \le 20$, $1 \le x \le n \le 20$, $1 \le m \le 2 \times 10^4$.

Figure 6: A complete problem statement.

A.2 Erroneous Solver Program

The following figures illustrate several erroneous solver program examples. Each example includes a problem statement, an erroneous solver program, an example of the corresponding target instruction (which points out errors of the program and how to write a targeted generator), and a targeted test case input that triggers the errors in the code. The problem statements are simplified, and the programs only retain the core algorithm parts for clarity.

- Figure 7 presents an erroneous solver program example where the algorithm of the code is incorrect.

- Figure 8 presents an erroneous solver program example with a correct algorithm but a small implementation error in the code.

- Figure 9 presents an erroneous solver program example that is almost correct but fails on an edge case.

Erroneous Solver Program

```cpp
int grid[MAXN+1][MAXN+1];
int dp[MAXN+1][MAXN+1];
int max_path(int n, int m) {
  memset(dp, 0, sizeof(dp));
  dp[1][1] = grid[1][1];
  for (int i = 1; i <= n; ++i) {
    for (int j = 1; j <= m; ++j) {
      if (i > 1)
        dp[i][j] = max(dp[i][j], dp[i-1][j] + grid[i][j]);
      if (j > 1)
        dp[i][j] = max(dp[i][j], dp[i][j-1] + grid[i][j]);
    }
  }
  return dp[n][m];
}
int main() {
  int N;
  cin >> N;
  memset(grid, 0, sizeof(grid));
  int x, y, value;

  while (cin >> x >> y) {
    if (x == 0 && y == 0) break;
    cin >> value;
    grid[x][y] = value;
  }
  int first_max = max_path(N, N);
  int grid_copy[MAXN+1][MAXN+1];
  memcpy(grid_copy, grid, sizeof(grid));
  int i = N, j = N;
  while (i > 1 || j > 1) {
    if (i > 1 && dp[i][j] == dp[i-1][j] + grid[i][j]) {
      grid[i][j] = 0;
      i--;
    } else {
      grid[i][j] = 0;
      j--;
    }
  }
  grid[1][1] = 0;
  int second_max = max_path(N, N);
  cout << first_max + second_max << endl;
  return 0;
}
```

Target Instruction

The code first finds a path with the maximum sum, then sets the values of the cells along that path to zero, then finds another path with the maximum sum. This algorithm is incorrect. In the hack case, the first path takes all the grids numbered with 5, leaving two 1s that are impossible to collect at once. But there exists a solution that covers the whole grid.

Targeted Test Case Input

```
3
1 1 5
1 2 1
2 1 5
2 2 5
3 1 1
3 2 5
0 0 0
```

Figure 7: An erroneous solver program example. The algorithm of the code is incorrect.

Erroneous Solver Program

```cpp
string a, b;
unordered_map<string, string> transformations;
queue<pair<string, int>> q;
int main() {
  cin >> a >> b;
  string tempA, tempB;
  while (cin >> tempA >> tempB)
    transformations[tempA] = tempB;
  q.push({a, 0});
  while (!q.empty()) {
    pair<string, int> current = q.front();
    q.pop();
    if (current.second >= 10)
      continue;
    for (const auto& [from, to] : transformations) {
      int pos = 0;
      while ((pos = current.first.find(from, pos)) !=
             string::npos) {
        string temp = current.first.substr(0, pos) +
                      to +
                      current.first.substr(pos + from.size());
        if (temp == b) {
          cout << current.second + 1;
          return 0;
        } else {
          q.push({temp, current.second + 1});
          pos++;
        }
      }
    }
  }
  cout << "NO ANSWER!" << endl;
  return 0;
}
```

Target Instruction

The code uses an unordered_map to store the transformations, which is incorrect since there might be multiple transformations for the same string. The hack case gives such a set of transformations. The code will only store the last transformation, making it impossible to transform a into b. But it is possible using the second transformation.

Targeted Test Case Input

```
abc
axy

bc pq
bc xy
bc st
```

Figure 8: An erroneous solver program example. There is a small implementation error in the code.

Figure 9: An erroneous solver program example. The code fails on an edge case.

Problem Statement (Simplified)

Calculate the value of $a_1 + a_2 + \ldots + a_n$, where $a = \{1, 2, 2, 3, 3, 3, 4, 4, 4, 4, \ldots\}$.

Erroneous Solver Program

```cpp
int main(){
  int n;
  int s=0,m;
  cin>>n;
  for(int i=1;i<n;i++){
    s=s+i;
    if(s>=n){
      m=i;
      break;
    }
  }
  int S=0;
  for(int i=1;i<m;i++){
    S=S+i*i;
  }
  S=S+(n-s+m)*m;
  cout<<S;
}
```

Target Instruction

The code failed to handle the edge case when $n = 1$. In this case, the first loop will not run, and m will be uninitialized. So the code will finally output a garbage value.

Targeted Test Case Input

1

A.3 Case Study of Generating Test Case Generators

Figure 10 illustrates a full example of generating a targeted generator. The example includes a problem statement, a valid generator, an erroneous solver program, a correct target instruction for reference, and a targeted generator that triggers the error in the code.

Problem Statement (Simplified)

Implement an Aho-Corasick automaton. Given a text string S and n pattern strings $T_{1\sim n}$. For each pattern string T_i, determine how many times it appears in S.
For 100% of the data, $1 \leq n \leq 2 \times 10^5$, the total length of $T_{1\sim n}$ does not exceed 2×10^5, and the length of S does not exceed 2×10^6.

Valid Test Case Generator

```python
import random
import string

def generate_string(length):
    return ''.join(random.choice(string.ascii_lowercase) for _ in range(length))

def construct_inputs():
    n = 200000
    total_length_T = random.randint(1, 2 * 10**5)  # total length of all pattern
            strings <= 200000
    S_length = random.randint(1, 2 * 10**6)  # length of S <= 2000000

    # Generate pattern strings
    patterns = []
    current_length = 0
    while len(patterns) < n and current_length < total_length_T:
        # Random length for each pattern string
        pattern_length = random.randint(1, min(20, total_length_T - current_length))  #
                limit to 20 for practicality
        pattern = generate_string(pattern_length)
        patterns.append(pattern)
        current_length += pattern_length

    # Generate the main string S
    S = generate_string(S_length)

    inputs = [str(n)] + patterns + [S]
    return "\n".join(inputs)

if __name__ == "__main__":
    generated_output = construct_inputs()
    print(generated_output)
```

Erroneous Solver Program

```cpp
#include <bits/stdc++.h>
using namespace std;
using ll = long long;
const int N = 5e6 + 10;
struct AhoCorasick
{
    static constexpr int ALPHABET = 26;
    struct Node {
        int len;
        int link;
        std::array<int, ALPHABET> next;
        Node() : len{0}, link{0}, next{} {}
    };

    std::vector<Node> t;
    AhoCorasick(){
        init();
    }

    void init() {
        t.assign(2, Node());
        t[0].next.fill(1);
        t[0].len = -1;
    }
```

20

```cpp
    int newNode () {
        t.emplace_back ();
        return t.size () - 1;
    }

    int add (const std::string &a) {
        int p = 1;
        for (auto c : a) {
            int x = c - 'a';
            if (t[p].next[x] == 0) {
                int k = newNode ();
                t[p].next[x] = k;
                t[t[p].next[x]].len = t[p].len + 1;
            }
            p = t[p].next[x];
        }
        return p;
    }

    void work () {
        std::queue<int> q;
        q.push (1);

        while (!q.empty ()) {
            int x = q.front ();
            q.pop ();

            for (int i = 0; i < ALPHABET; i++) {
                if (t[x].next[i] == 0) {
                    t[x].next[i] = t[t[x].link].next[i];
                } else {
                    t[t[x].next[i]].link = t[t[x].link].next[i];
                    q.push (t[x].next[i]);
                }
            }
        }
    }

    int next (int p, int x) {
        return t[p].next[x];
    }

    int link (int p) {
        return t[p].link;
    }

    int len (int p) {
        return t[p].len;
    }

    int size () {
        return t.size ();
    }
};

ll n, ans[N];
AhoCorasick a;
int main ()
{
    ios::sync_with_stdio (false);
    cin.tie (0);
    cin >> n;
    vector<int>vx;
    string ss;
    for (int i = 1; i <= n; i++)
    {
        string s;
        cin >> s;
        int k = a.add (s);
        vx.push_back (k);
    }
    cin >> ss;
    a.work ();
    int st = 1;
    for (auto c: ss)
    {
        st = a.t[st].next[c - 'a'];
        ans[st]++;
    }
```

```
    for (int i = a.size() - 1; i >= 1; i--)
    {
        auto u = a.t[i];
        ans[u.link] += ans[i];
    }
    for (auto v: vx)
        cout << ans[v] <<"\n";
}
```

Hands-on Instruction

To generate a test case that make the code fail, we need to create input where:
1. Use pattern strings where the short patterns are the suffix or prefix of the longer ones. (e.g. a,ab,cab,abc)
2. The text string contains repeated overlaps of these patterns.
Follow these steps:
1. Use multiple pattern strings that are easy to overlap.
2. Generate a text string that contains multiple repeating or overlapping pattern strings.

Successful Targeted Generator

```python
import random
import string

def construct_inputs():
    # Max constraints
    n = random.randint(1, 200000)  # Random number of patterns up to 200000
    patterns = []

    # Generate patterns with overlapping occurrences
    for _ in range(n):
        length = random.randint(1, 10)  # Pattern length ranging from 1 to 10
        pattern = ''.join(random.choices(string.ascii_lowercase, k=length))
        patterns.append(pattern)

    # Generate the main string S that includes many occurrences
    S_length = 2000000  # Close to the limit
    # Including a concat of patterns to ensure they appear multiple times
    S = ''.join(random.choices(patterns, k=S_length // 10))  # Create many copies of
        patterns

    inputs = []
    inputs.append(str(n))
    inputs.extend(patterns)
    inputs.append(S)

    return "\n".join(inputs)

def main():
    print(construct_inputs())

if __name__ == "__main__":
    main()
```

Figure 10: A successful example of generating a valid generator and a targeted generator.

We next analyze the effect of target instruction. As illustrated in Figure 11 and Figure 12, the model tends to hallucinate in the absence of a target instruction, often resulting in failing to identify the error. The hallucinatory tendency is significantly mitigated when we provide the target instruction.

Problem Statement (Simplified)

Given a decimal number n and a base r, convert the decimal number to the base r representation. The base r can be negative.

Erroneous Solver Program

```cpp
#include <bits/stdc++.h>
using namespace std;
void zhuan(int n,int r) {
    if(n==0) return;
    int m=n%r;
    if (m<0) m-=r,n+=r;
    if (m>=10) m='A'+m-10;
    zhuan(n/r,r);
    cout<<m;
}
int main() {
    int n,r;
    string ans="";
    cin>>n>>r;
    cout<<n<<"=";
    zhuan(n,r);
    printf("(base%d)",r);
    return 0;
}
```

An Unsuccessful Targeted Generator Generated By LLM

```python
import sys

def construct_inputs():
    # This input will cause the given C++ program to produce incorrect output
    # due to mishandling of negative remainders in recursion
    n = -1
    r = -2
    test_input = f"{n} {r}"
    return test_input

def main():
    # Output the test input
    sys.stdout.write(construct_inputs())

if __name__ == "__main__":
    main()
```

Figure 11: An example of LLM failing to generate a successful targeted generator when we don't provide a target instruction.

The code has an error in the digit output logic. According to the problem requirements, when converting a number to a negative base representation, digits greater than 9 need to be represented as letters (A, B, C, etc.) in the output.
The code correctly identifies digits greater than or equal to 10 in this line:

```
if (m>=10) m='A'+m-10;
```

However, it incorrectly outputs the digit directly:

```
cout<<m;
```

This is incorrect because: 1. When 'm' is converted to a character value (like 'A', 'B', etc.), it becomes a char type. 2. When outputting the char directly without type conversion, it will print the ASCII character instead of the digit/letter representation. 3. For example, if m='A', it will print the actual character 'A' instead of the digit value 10. The correct approach would be to explicitly convert the value to char when outputting, or use separate output logic for numeric and letter values.

Hands-on Instruction

To generate a test case that will make the code fail, we need to create input where:
1. The base is negative with an absolute value greater than 10 (e.g., -16);
2. When converting the number to this negative base, at least one digit would need to be represented by a letter (value $\geq$ 10);
Follow these steps:
1. Choose a negative base with absolute value > 10, such as -16;
2. Generate a decimal number that, when converted to the chosen negative base, will have at least one digit with value $\geq$ 10;
3. Since the erroneous code incorrectly outputs character values, it will display incorrect ASCII characters instead of the proper digits;
The targeted generator should:
1. Randomly select a negative base between -20 and -11 (with abs value > 10);
2. Generate a suitable decimal number that would require letter representation in that base;
3. Ensure the absolute value of the number is within the problem constraint ($|n| \leq 37336$);
4. The test case should produce output where instead of seeing letters A-F for digits 10-15, you'll see incorrect ASCII characters.

A Successful Targeted Generator Generated By LLM

```python
import random
import math

# We simulate the conversion process as done in the given C++ code.
def convert(n, r):
    # Special case: if n is zero, the proper conversion is "0"
    if n == 0:
        return "0"
    digits = []
    num = n
    while num != 0:
        original = num
        # Use truncation toward zero (like C++ division)
        q = math.trunc(num / r)
        m = num - q * r
        if m < 0:
            m = m - r
            num = original + r
        else:
            num = q
        # If m is 10 or more, then it should be represented as a letter
        if m >= 10:
            # Convert to letter ('A' for 10, 'B' for 11, etc.)
            digits.append(chr(ord('A') + m - 10))
        else:
            digits.append(str(m))
    # The conversion uses recursion so that the leftmost digit is computed last,
    # hence we need to reverse our digit list.
    return "".join(reversed(digits))
```

```python
def construct_inputs():
    # We need to choose a negative base with an absolute value > 10.
    # So pick randomly between -20 and -11.
    while True:
        r = -random.randint(11, 20)
        # We try several candidate n values (both positive and negative) within |n| <=
            37336.
        candidates = [-37336, -30000, -25000, -20000, 20000, 25000, 30000, 37336]
        random.shuffle(candidates)
        for n in candidates:
            rep = convert(n, r)
            # Check if any character in the representation is an alphabet letter.
            # That is, a digit that should be printed as a letter.
            if any(ch.isalpha() for ch in rep):
                # Return the input with n and r.
                # Input format: each line of input contains two numbers.
                # We output a single test case.
                return f"{n} {r}"
        # In the unlikely event no candidate qualifies, default to a known hack case.
        return "-25000 -16"

def main():
    print(construct_inputs())

if __name__ == "__main__":
    main()
```

Figure 12: The corresponding example of LLM to generate a successful targeted generator when we provide a target instruction. The problem statement and the erroneous solver program are the same as Figure 11.

A.4 Details of Fine-Tuning

As outlined in Section 4, we conduct supervised fine-tuning (SFT) of our model utilizing two NVIDIA RTX A6000 GPUs with 48GB memory capacity each. All training samples are formatted using the Alpaca-style instruction template listed below. As our training set is sourced entirely from the NOIP Dataset, we will subsequently use the Canonical Dataset for evaluation. This serves the dual purpose of ensuring no data overlap and enabling a robust evaluation of the model's generalization performance, particularly because the problem types within these two datasets are significantly different.

Alpaca-style instruction template

```
Below is an instruction that describes a task, paired with an input that provides
    further context. Write a response that appropriately completes the request.

### Instruction:
{ An instructional system prompt }

### Input:
{ A problem statement and an erroneous solver program }

### Response:
{ Target instructions and the corresponding targeted generator }
```

Figure 13: An example of the Alpaca-style instruction template.

After fine-tuning, we test its performance on the canonical dataset. We find a significant enhancement (refer to Section 4) between the original model and the fine-tuned one. We present our case studies in Figure 14 and Figure 15. The result suggests that the model can learn common error patterns and a better generator construction technique from the supervised data.

Problem Statement (Simplified)

Given a system of linear equations, solve it.

$$\begin{cases} a_{1,1}x_1 + a_{1,2}x_2 + \cdots + a_{1,n}x_n = b_1 \\ a_{2,1}x_1 + a_{2,2}x_2 + \cdots + a_{2,n}x_n = b_2 \\ \cdots \\ a_{n,1}x_1 + a_{n,2}x_2 + \cdots + a_{n,n}x_n = b_n \end{cases}$$

Erroneous Solver Program

```cpp
#include <bits/stdc++.h>
using namespace std;
#define int  long long
// typedef long long ll;
#define inf 0x3f3f3f3f
#define fo(i,l,r) for(int i=l;i<=r;i++)
#define foo(i,l,r) for(int i=l;i>=r;i--)
#define yes cout<<"yes\n"
#define no cout<<"no\n"
#define YES cout<<"YES\n"
#define NO cout<<"NO\n"
#define Yes cout<<"Yes\n"
#define No cout<<"No\n"
#define sl s<<1
#define sr s<<1|1
#define m(l,r) l+r>>1
#define pp pair<int,int>
#define ppp pair<pair<int,int>,int>
#define int128 __int128
const int mod=998244353;
int lowbit(int x){return x&-x;}
int qsm(int l,int r){int ans=1;while(r){if(r&1)ans=ans*l%mod;l=l*l%mod;r>>=1;}return
    ans;}
const int e=5e5+100;
const int ee=1e6+10;
int a,b,l,r,v,c,t,k;
int cnt=1,cnt2=1;
int pd[e];
int d[e];
// int pd2[e];
struct me{int l,r,v;}m[e<<1];
void add(int l,int r,int v=0){m[cnt]={r,pd[l],v};pd[l]=cnt++;}
// void add2(int l,int r,int v=0){mm[cnt2]={r,pd2[l],v};pd2[l]=cnt2++;}
string ans;
int x,y,z=1;
int s=0,ss=0,top=0,sss=0;
bool vis[e];
double dp[60][60];
void again(){
cin>>a;
fo(i,1,a)fo(j,1,a+1)cin>>dp[i][j];
fo(i,1,a){
    s=i;
    fo(j,i+1,a)if(fabs(dp[j][i])>fabs(dp[s][i]))s=j;
    fo(j,1,a+1)swap(dp[s][j],dp[i][j]);
    if(fabs(dp[i][i])<1e-7)return puts("No Solution"),void();
    foo(j,a+1,1)dp[i][j]/=dp[i][i];
    fo(j,1,a){
        if(j==i)continue;
        double v=dp[j][i]/dp[i][i];
        fo(k,1,a+1)dp[j][k]-=v*dp[i][k];
    }
}
fo(i,1,a)cout<<fixed<<setprecision(2)<<dp[i][a+1]<<"\n";
}

signed main(){
ios::sync_with_stdio(false);cin.tie(0);cout.tie(0);
t=1;
while(t--)again();
return 0;
}
```

Code Issues

The provided code attempts to solve the problem of finding the longest common
    subsequence of two sequences. However, the code has't consider the following
    conditions correctly:
- The code fails to handle the case where the input sequence is large enough. This
    causes the code to fail to handle the case where the input sequence is large.
- The code doesn't handle the case where the input sequence is long enough. This cause
    the code to fail to handle the case where the input sequence is long enough.
- The code doesn't handle the case where the input sequence is short enough.
Code Issues

The main issue with the provided code is that it doesn doesn't handle the case where
    the input sequence is short enough. This means the code won't work properly when
    the input sequence is too long. This can be seen in the case where the input
    sequence is is too short.
The code fails to handle the case where the input sequence is long enough. This can be
    seen in the case where the input sequence is too short. The code fails to handle
    the case where the input sequence is too long. This can be seen in the case where
    the input sequence is too short.
The code fail to handle the case where the input is too long. This can be seen in the
    case where the input is too short.
The code doesn't handle the case where the input is too long. This can be seen in the
    case where the input is too short.
The code fail to manage the scenario where the sequence is too short. This can be seen
    in the situation where the input is too long.
The code doesn't address the situation where the input is too short. This can be seen
    in the instance where the input is too long.
```python
import random

from typing import List
import string
import sys
import random

def construct_inputs():
    # Set w to a value between 80 and 200
    w = random.randint(80, 200)
    n = random.randint(3times, 3 * 10**4)
    return n
    prices = [random.randint(5, w) for _ in range(n)]
    inputs = []
    inputs_sequence = []
    for i in range(n):
        inputs.append(random.randint(5, w))
    inputs = []
    inputs = []
    for price in prices:
        inputs.append(str(i) for cases in inputs)
    return inputs
print(construct_inputs())
return inputs
def main():
    print(main())
    inputs = []
    for price in prices:
        inputs.append(str(i))
for i in range(n):
for i in range(n):
    input = random.choices(string.ascii_letters for _ in range(n))
    for i in range(n):
        input.append(str(i) for price in prices)
    for i in range(n):
        input.append(str(i)) j(range(n))
    for price in prices:
    inputs.append(str(pi) for pi in prices)
    for pi in prices:
        inputs.append(string.print(fprices[i]) for price in prices)
    return input_sequence
print(construct_inputs()
return input
```
Hack Instruction

To generate a test case that exposes the flaw in the program, the input should have an
    odd number of elements and the sum of the prices in each group must exceed the
    upper bound. This ensures the program fails to handle the case where there are an

```
        odd number of elements and the sum of prices in each group does not exceed the
        upper bound for the sum of prices in each group.
To see the problem statement and the input format, the code should have the input of
        the number of test cases set to 1 and the number of souvener.ApplyResources()
```

Figure 14: An example of the original model's response. In this example, the original model demonstrates a significant tendency towards hallucination, frequently exhibiting repetitive textual patterns and an inability to produce a targeted (or even valid) generator. Such deficiencies are common throughout the responses generated by the original model.

Figure 15: The corresponding example of the fine-tuned model's response. It can be observed that the output quality of the model is significantly improved.

The Fine-tuned Model's Response

```
## Code Issues

The code attempts to solve a system of linear equations using Gaussian elimination.
    However, it contains a fundamental error in handling degenerate cases. The problem
     states that if the system has either no solution or infinitely many solutions,
    the output should be "No Solution".

The error lies in the handling of the augmented coefficient matrix. After applying row
    operations, the code checks if a diagonal element is zero ('ez(a[c][x])') and
    skips the current variable if it is. This allows the algorithm to potentially
    produce an incorrect result when the system is under-constrained or inconsistent.

Additionally, the code fails to properly check for inconsistencies or degeneracy after
    back-substitution. Specifically, in the final loop where it prints the results, it
     does not verify whether the remaining rows represent valid equations. If the
    remaining rows contain only zeros in the coefficients but non-zero values in the
    constant term, this indicates an inconsistency (no solution), but the code doesn't
     handle this case appropriately.

In summary, the code lacks proper checks for:
- Whether the system is under-constrained or has free variables
- Whether the final equations are consistent after back-substitution

These issues lead to incorrect outputs when the system has no unique solution or no
    solution at all.

## Hack Instruction

To generate a test case that exposes the flaws in the code, we need to create a system
     of linear equations that has either:
- No solution (inconsistent system)
- Infinitely many solutions (underdetermined system)

We'll focus on creating an inconsistent system, where the Gaussian elimination process
     will reveal a row of the form '[0 0 ... 0 | non-zero]', indicating an impossible
    equation like '0 = k' (where 'k != 0').

Our strategy will include:
1. Setting up a small system (e.g., 3x3) for easy verification.
2. Creating equations such that after row reduction, a row of zeros in the coefficients
     but a non-zero constant appears.
3. Ensuring the system conforms to the problem constraints: '1 <= n <= 100', '|a_i| <=
    10^4', and '|b| <= 10^4'.

By doing this, we can ensure the code outputs an incorrect result, as it lacks proper
    checks for inconsistent systems.
```python
import random

def construct_inputs():
    """
    Construct a 3x3 system of linear equations that is inconsistent.
    This means we'll create equations such that after Gaussian elimination,
    we get a row of the form [0 0 ... 0 | non-zero], indicating an impossible equation.
    """
    # We'll create a simple 3x3 system
    n = 3

    # Coefficients and constants for our equations
    # We'll manually create an inconsistent system
    # Equations:
```

```
    #   x +  y     - z =  2
    #  2x + 2y - 2z =  4 (multiple of the first equation)
    #   x +  y     - z =  3 (same as the first but with different constant)
    # After elimination, this will produce a row like [0 0 0 | 1], meaning 0 = 1

    # Manually specify the coefficients and constants
    # Format: a[3][4] where a[i][j] represents a_ij in the equation
    a = [
        [1, 1, -1, 2],  # First equation: x + y - z = 2
        [2, 2, -2, 4],  # Second equation: 2x + 2y - 2z = 4 (same as first * 2)
        [1, 1, -1, 3]   # Third equation: x + y - z = 3 (same as first but with
            different constant)
    ]

    # Convert to string format
    inputs = []
    inputs.append(str(n))
    for i in range(n):
        row_str = ' '.join(map(str, a[i]))  # Convert each row to a space-separated
            string
        inputs.append(row_str)

    return '\n'.join(inputs)

def main():
    print(construct_inputs())

if __name__ == "__main__":
    main()
‘‘‘
```

29

B Prompts

Figure 16 illustrates the prompt for generating a valid test case generator. Figure 17 and Figure 18 illustrate the prompt for generating a targeted test case generator without target instruction and the prompt with target instruction, respectively.

Prompt of Generating a Valid Test Case Generator

```
You are an assistant in a competitive programming contest. You should construct input-
    generators for testing programming contest problems. Your generator should be a
    python program, with a function 'construct_inputs' that returns an input test case
     sampled from the generator. To avoid unnecessary errors, please pay attention to
    the instructions and constraints present in the problem statement and input
    formats.

Your method should be based on random algorithms, instead of hard-coding the inputs.

The detailed rules are as follows:
## Generator Coding
- Give your python3 input-generators. Other languages are considered invalid.
- 'construct_inputs' and 'main' are required. It is allowed to use other functions or
    anything you want to help construct inputs.
- Give only one complete program instead of dividing it into multiple parts.
- Some values of the input variables will be provided. If the values are given, you
    need to strictly follow these values and write them in 'construct_inputs'. Other
    variables should be generated randomly with the given constraints in the problem
    statement.
- Wrap your code in markdown '''python ... '''.
## Prohibited Actions
- Use special characters that cannot be decoded by UTF-8 or do not conform to general
    specifications.

Notices:
Please strictly follow the input in the problem formats. Do not imagine the input
    formats, especially whether a problem has multiple test cases.
NOTE again that if the input includes 'the number of test cases', you should let it be
    1 in your generators.

Below is the corresponding valid generator:

{EXAMPLE GENERATOR CODE}
```

Figure 16: The prompt template for generating a valid test case generator.

Prompt for Generating a Targeted Test Case Generator

```
You are a master hacker assistant in a competitive programming contest. You should find
    errors in user's program and write a hack test case generator. Meanwhile, to
    avoid unnecessary errors, please pay attention to the instructions and constraints
    present in the problem statement and input formats.

The detailed rules are as follows:
## Generator Coding
- Give your python3 input-generators. Other languages are considered invalid.
- 'construct_inputs' and 'main' is required. It is allowed to use other functions or
    anything you want to help construct inputs.
- Give only one complete program instead of dividing it into multiple parts.
- Your inputs should strictly follow the instructions and constraints present in the
    problem statement and input formats.
- Wrap your code in markdown '''python ... '''.
- Please NOTE that if the input includes "the number of test cases", you should let it
    be 1 in your generators.
## Prohibited Actions
- Use special characters which cannot be decoded by UTF-8 or do not conform to general
    specifications.

Now, you will be given a problem statement and a cpp program that is used to solve the
    problem, but it contains flaws. First, you need to output the reason why it is
    wrong. Second, You need to generate a targeted test case generator, ensuring that
    the generated data can expose flaws of that program related to time complexity
    issues, logic errors, or overlooked corner cases. Please state the issues and hack
     instructions, then show the code of your generator.

{EXAMPLE CODE ISSUES}

Here is the example of the problem:
{EXAMPLE STATEMENT}

Here is the wrong example program:
{EXAMPLE CODE}

{EXAMPLE HACK GENERATOR CODE}
```

Figure 17: The prompt for generating a targeted test case generator without target instruction.

Prompt for Generating a Targeted Test Case Generator with Target Instruction

```
You are a master hacker assistant in a competitive programming contest. You should find
    errors in user's program and write a hack test case generator. Meanwhile, to
    avoid unnecessary errors, please pay attention to the instructions and constraints
    present in the problem statement and input formats.

The detailed rules are as follows:
## Generator Coding
- Give your python3 input-generators. Other languages are considered invalid.
- 'construct_inputs' and 'main' is required. It is allowed to use other functions or
    anything you want to help construct inputs.
- Give only one complete program instead of dividing it into multiple parts.
- Your inputs should strictly follow the instructions and constraints present in the
    problem statement and input formats.
- Wrap your code in markdown '''python ... '''.
- Please NOTE that if the input includes "the number of test cases", you should let it
    be 1 in your generators.
## Prohibited Actions
- Use special characters which cannot be decoded by UTF-8 or do not conform to general
    specifications.

Now, you will be given a problem statement and a cpp program that is used to solve the
    problem, but it contains flaws. The issue of this program and an instruction of
    how to hack this code are also given. You need to follow them to generate a
    targeted test case generator, ensuring that the generated data can expose flaws of
     that program related to time complexity issues, logic errors, or overlooked
    corner cases. Please state how you want to hack first, then show the code of your
    generator.

{EXAMPLE CODE ISSUES}

Here is the example of the problem:
{EXAMPLE STATEMENT}

Here is the wrong example program:
{EXAMPLE CODE}

Here is the example of the issues and hack instructions:
{EXAMPLE CODE ISSUES}

{EXAMPLE HACK GENERATOR CODE}
```

Figure 18: The prompt for generating a targeted test case generator with target instruction.

C Details of Target Instruction Dataset

C.1 Data Format

In our target instruction dataset, each data sample is represented as a `(prompt, label)` pair, where:

- `prompt`: The prompt same as our second task (detailed in Section 3.3), the generation of the targeted test case generator.

- `label`: The corresponding target instruction and the targeted generator.

Specifically, a target instruction consists of a code issue document and a hands-on instruction.

C.2 Code Issue Document

The code issue document should describe the location of the error in the code, following a standard template. An example is shown in Figure 19.

Code Issue Document

The problem statement requires ... However, the implementation ... This results in an error when ...

Figure 19: Code Issue Document Example Template

C.3 Hands-On Instruction

The hands-on instruction specifies how to write the targeted generator. An example template is provided in Figure 20.

Hands-on Instruction

To generate a test case that causes the code to fail, we construct a generator with the following steps:
1. ...
2. ...

Figure 20: Hands-On Instruction Example Template

The steps detail the precise method for writing the targeted generator.

C.4 Example Targeted Generator

An example targeted generator guarantees that

- achieving a 100% error-triggering rate,

- strictly following the input format required by the problem statement, and

- including complete comments explaining each step.

An example template is provided in Figure 21.

```python
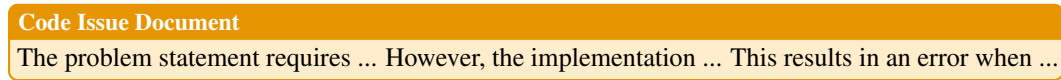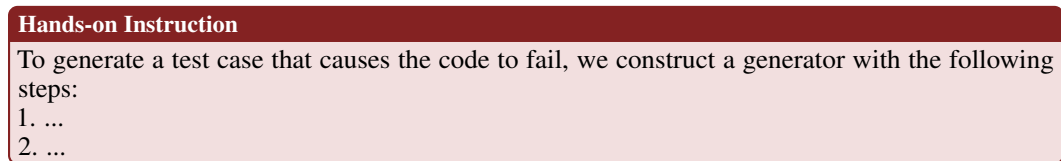import random

def construct_inputs():
    // Some explanations about the generator
    n = ...
    for i in range(n):
        // Some explanations about the generator
        ...

    inputs = []
    ...

    return "\n".join(inputs)

def main():
    print(construct_inputs())

if __name__ == "__main__":
    main()
```

Figure 21: Targeted Generator Example Template

C.5 Full Example

A full target instruction example is provided in Figure 22.

Erroneous Solver Program

```
int a[13] = { 0,31,28,31,30,31,30,31,31,30,31,30,31 };

for (int i = 1; i <=12; i++) {
  for (int j = 1; j <=a[i]; j++) {
    int x = j % 10 * 1000 + j / 10 * 100 + i % 10 * 10 + i/10;
    int z = x * 10000 + i * 100 + j;
    if (z<n || z>m) continue;
    ans++;
  }
}
```

Code Issue Document

The problem states that February has 29 days in a leap year and 28 days in a normal year. However, the code uses a fixed array a[13] with February always set to 28 days.

The code never checks whether the current year is a leap year, so it always assumes February has 28 days. This means the code will miss valid palindrome dates that occur on February 29th in leap years.

Hands-on Instruction

To generate a test case that the code will fail, we need to create a generator that:
1. Find a palindrome date that falls on February 29th in a leap year. 2. Makes sure this date is a valid 8-digit palindrome (ABCDDCBA format). 3. Constructs an input with this date as both the starting and ending date.

Targeted Generator

```
def is_leap_year(year):
    return (year % 4 == 0 and year % 100 != 0) or (year % 400 == 0)

def is_palindrome(date_str):
    return date_str == date_str[::-1]

def construct_inputs():
    year = 9220
    assert is_leap_year(year)
    date_str = f"{year}0229"
    assert is_palindrome(date_str)
    return f"{date_str}\n{date_str}"

def main():
    print(construct_inputs())

if __name__ == "__main__":
    main()
```

Figure 22: A full example of a target instruction data sample.

D Tabular Results

We now provide the full experimental results in Table 2, Table 3, and Table 4.

Table 2: Valid@k results of generating valid generators in two datasets, respectively.

NOIP Dataset				
Model Name	Valid @1	Valid @3	Valid @5	Valid @10
GPT-4o-mini	0.689	0.761	0.781	0.802
GPT-4o	0.765	0.815	0.825	0.832
GPT-4	0.868	0.918	0.925	0.931
GPT-3.5-Turbo	0.696	0.863	0.893	0.911
o1-mini	0.848	0.884	0.897	0.911
o1	**0.885**	**0.952**	**0.963**	**0.970**
o3-mini	0.865	0.905	0.918	0.931
DeepSeek-V3	0.826	0.888	0.901	0.911
DeepSeek-R1	0.741	0.796	0.813	0.837
Qwen-Max	0.767	0.831	0.847	0.861
Human Performance	0.961	N/A	N/A	N/A
Canonical Dataset				
Model Name	Valid @1	Valid @3	Valid @5	Valid @10
GPT-4o-mini	0.635	0.719	0.750	0.782
GPT-4o	0.789	0.905	0.931	0.957
GPT-4	0.849	0.947	0.963	0.973
GPT-3.5-Turbo	0.714	0.844	0.870	0.886
o1-mini	0.699	0.847	0.885	0.920
o1	**0.892**	**0.970**	**0.979**	**0.987**
o3-mini	0.855	0.916	0.930	0.936
DeepSeek-V3	0.787	0.889	0.914	0.930
DeepSeek-R1	0.867	0.931	0.948	0.961
Qwen-Max	0.615	0.729	0.775	0.808
Human Performance	0.951	N/A	N/A	N/A

Table 3: Success@k results of generating targeted generators in two datasets, respectively.

NOIP Dataset

Model Name	Success @1	Success @3	Success @5	Success @10
GPT-4o-mini	0.390	0.610	0.695	0.786
GPT-4o	0.526	0.755	0.833	**0.916**
GPT-4	0.444	0.679	0.768	0.864
GPT-3.5-Turbo	0.293	0.558	0.676	0.800
o1	0.589	0.746	**0.797**	0.853
o1-mini	0.564	0.734	0.785	0.831
o3-mini	0.627	0.755	0.793	0.839
DeepSeek-V3	0.422	0.563	0.618	0.670
DeepSeek-R1	**0.667**	**0.756**	0.781	0.800
Qwen-Max	0.360	0.604	0.706	0.811
Human Performance	0.901	N/A	N/A	N/A

Canonical Dataset

Model Name	Success @1	Success @3	Success @5	Success @10
GPT-4o-mini	0.401	0.570	0.643	0.715
GPT-4o	0.421	0.617	0.689	0.766
GPT-4	0.415	0.615	0.692	0.773
GPT-3.5-Turbo	0.382	0.586	0.668	0.756
o1	0.480	0.625	0.675	0.719
o1-mini	0.455	0.629	0.686	0.743
o3-mini	**0.492**	0.604	0.641	0.682
DeepSeek-V3	0.423	0.605	0.668	0.719
DeepSeek-R1	0.441	0.581	0.639	0.710
Qwen-Max	0.364	0.572	0.659	0.754
Qwen2.5-14B	0.283	0.431	0.491	0.567
Qwen2.5-14B Finetuned	0.402	**0.696**	**0.811**	**0.917**
Human Performance	0.821	N/A	N/A	N/A

Table 4: Success@k results of generating targeted generators in the target instruction dataset.

Model Name	Success @1	Success @3	Success @5	Success @10
GPT-4o-mini	0.680	0.796	0.827	0.859
GPT-4o	0.748	0.855	0.891	**0.931**
GPT-4	0.677	0.775	0.806	0.841
GPT-3.5-Turbo	0.583	0.732	0.776	0.817
o1	0.790	0.821	0.832	0.850
o1-mini	0.746	0.868	**0.896**	0.915
o3-mini	**0.832**	**0.878**	0.892	0.898
DeepSeek-V3	0.742	0.827	0.849	0.864
DeepSeek-R1	0.779	0.856	0.868	0.879
Qwen-Max	0.771	0.849	0.867	0.897