**OpenCodeInterpreter:** Integrating Code Generation with Execution and Refinement

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https://opencodeinterpreter.github.io

Abstract

The introduction of large language models has significantly advanced code generation. However, open-source models often lack the execution capabilities and iterative refinement of advanced systems like the GPT-4 Code Interpreter. To address this, we introduce OpenCodeInterpreter, a family of open-source code systems designed for generating, executing, and iteratively refining code. Supported by CodeFeedback, a dataset featuring 68K multi-turn interactions, OpenCodeInterpreter integrates execution and human feedback for dynamic code refinement. Our comprehensive evaluation of OpenCodeInterpreter across key benchmarks such as HumanEval, MBPP, and their enhanced versions from EvalPlus reveals its exceptional performance. Notably, OpenCodeInterpreter-33B achieves an accuracy of 83.2 (76.4) on the average (and plus versions) of HumanEval and MBPP, closely rivaling GPT-4’s 84.2 (76.2) and further elevates to 91.6 (84.6) with synthesized human feedback from GPT-4. OpenCodeInterpreter brings the gap between open-source code generation models and proprietary systems like GPT-4 Code Interpreter.

1 Introduction

Code generation has been a pivotal challenge within computer science for several decades. Recently, the landscape of code generation has been revolutionized by the advent of large language models (LLMs) pre-trained on extensive code corpora (Nijkamp et al., 2022; Christopoulou et al., 2022; Zheng et al., 2023; Li et al., 2023a; Wang et al., 2023c; Roziere et al., 2023; Guo et al., 2024). These models have showcased remarkable capabilities in generating code that accurately aligns with user intents, thus providing substantial support for software development (GitHub, 2023).

To unleash the capabilities of pre-trained code models, instruction-tuning methods have been de-
developed. For instance, CodeAlpaca (Chaudhary, 2023) comprises 20K code instructions automatically generated by applying self-instruct (Wang et al., 2023b) to ChatGPT, utilizing 21 seed tasks as the foundation. To further refine the coding proficiency of LLMs, Luo et al. (2023) introduces Code Evol-Instruct, a method that applies a variety of heuristics to enrich the complexity of initial code instructions, building upon the dataset provided by CodeAlpaca. Meanwhile, MagicCoder (Wei et al., 2023) employs a robust LLM to generate novel coding challenges, sourcing inspiration from a diverse range of open-source code snippets. Additionally, WaveCoder (Yu et al., 2023) implements an LLM generator-discriminator framework for creating code instruction data, offering customization and control over the data generation process.

Despite these advancements, current code models are constrained by their capacity to utilize feedback for refinement. Essentially, feedback can have two forms: (1) execution feedback, which includes execution outputs and diagnostics, and (2) human feedback, comprising follow-up guidance or instructions from users. Execution feedback plays a vital role in enabling models to rectify syntactic and logical errors, and human feedback aids models in better understanding user instructions, facilitating the generation of solutions that more closely align with user expectations.

To address these challenges, we propose OpenCodeInterpreter, a family of open-source code systems designed for generating, executing, and iteratively refining code. OpenCodeInterpreter is trained on our constructed Code-Feedback dataset, which features 68K multi-turn interactions between users, code models, and compilers. OpenCodeInterpreter uniquely integrates both execution and human feedback, employing compiler diagnostics to rectify errors and human insights to refine code generation. This approach allows OpenCodeInterpreter to produce solutions that are both technically sound and closely matched to user requirements, significantly boosting its overall performance.

Our thorough evaluation of OpenCodeInterpreter on widely recognized benchmarks, such as HumanEval (Chen et al., 2021), MBPP (Austin et al., 2021), and their augmented counterparts from EvalPlus (Liu et al., 2023), highlights its superior ability to generate and iteratively refine code, achieving exemplary standards of quality and functionality. Remarkably, OpenCodeInterpreter-33B secures an impressive accuracy of 83.2 (76.4) on the average (and plus versions) of HumanEval and MBPP, showcasing performance on par with GPT-4’s 84.2 (76.2). Furthermore, when augmented with synthesized human feedback from GPT-4, OpenCodeInterpreter’s performance notably increases to 91.6 (84.6). OpenCodeInterpreter thereby establishes a new benchmark in code generation, effectively narrowing the performance gap between open-source models and sophisticated proprietary systems like the GPT-4 Code Interpreter.

2 Code-Feedback

In this section, we detail the creation of our code instruction tuning dataset, Code-Feedback (Figure 2), designed to train OpenCodeInterpreter. Code-Feedback is crafted to meet specific criteria: 1) Diverse and challenging real-world queries: The dataset should encompass a wide range of queries derived from real-world coding tasks, presenting both diversity and complexity. 2) Multi-turn dialogue structure: Code-Feedback is structured as multi-turn dialogues, incorporating two types of feedback: execution feedback, which includes outputs and diagnostics from compilers, and human feedback, consisting of additional guidance or instructions from users. 3) Interleaved text and code responses: Each response is expected to provide responses that blend natural language explanations with code snippets, offering a holistic approach to solving coding queries.

To assemble a dataset that fulfills these desiderata, we have employed five distinct methods. Examples of these five categories can be found in Appendix E. The sources of our queries fall into two main categories: a variety of open-source datasets and coding challenges from LeetCode. In the next subsections, we will discuss how we develop data construction methods to meet the three aforementioned criteria from the two data sources.

2.1 Coding Queries from Open-source Data

We have aggregated 287k queries from four distinguished open-source code instruction tuning datasets: Magicoder-OSS-Instruct1, Python code subset of ShareGPT2, Magicoder-Evol-Instruct3, and Evol-Instruct-Code4. To refine this extensive

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1 hf.co/datasets/HuggingFaceH4/CodeAlpaca_20K
2 hf.co/datasets/ise-uiuc/Magicoder-OSS-Instruct-75K
3 hf.co/datasets/ajibawa-2023/Python-Code-23k
4 hf.co/datasets/ise-uiuc/Magicoder-Evol-Instruct-110K
5 hf.co/datasets/nickrosh/Evol-Instruct-Code-80k-v1
collection and isolate the most intricate and informative instructions, we employ a very capable open-source chat model, Qwen-72B-Chat (Bai et al., 2023), for a selective filtering process. This involves the LLM assessing each code query and its corresponding response within the compiled datasets on a complexity score from 1 to 5. Only the most challenging queries, with ratings of 4 or 5, were retained for our seed set, ensuring a focus on the most difficult instructions. To guarantee the robustness of our selection, this filtering operation is repeated with two distinct prompts (detailed in Appendix A), thereby solidifying the complexity of our final query selection. This meticulous process resulted in 156k high-quality single-turn code instructions as the challenging query pool. Detailed statistics of this data compilation are provided in Appendix A.

Subsequently, we describe three methods employed to transform this curated single-turn data into multi-turn dialogues enriched with both execution and human feedback.

**Singe-turn Packing.** A direct approach to crafting multi-turn data is to group single-turn query-response pairs into multi-turn formats. Inspired by in-context pre-training techniques (Shi et al., 2023), which consolidate similar sequences to foster model learning of dependencies among related documents, we merge similar single-turn query-response pairs to form multi-turn dialogues.

Utilizing the BERT-base embedding (Devlin et al., 2019), we convert queries into vectorized representations. For each query, the $k$-nearest neighbors algorithm is employed to identify its four closest counterparts. From these, we randomly select two or three to assemble multi-turn sequences. To maintain data uniqueness, once a query is chosen as a neighbor, it is exempt from future selections as a neighboring query, ensuring no single instruction is repeated across the dataset. Should a query’s potential neighbors have been previously utilized, that query is bypassed. This method results in the creation of 16.6K multi-turn instances derived from 105K single-turn instances.

**Interaction Simulation.** Gathering authentic human interaction data poses significant challenges. To replicate a realistic code interpreter usage scenario, we developed a simulator using GPT-3.5 and GPT-4. For each selected query, GPT-3.5 first generates a preliminary response from which we extract the code snippet and execute it. The outcome of this execution, along with any compiler diagnostics, is then fed into GPT-4 to elicit a follow-up response. This cycle is repeated until GPT-4 delivers what it deems a correct solution or until a maximum of three iterations is reached.

**Subsequently, we introduce simulated human feedback into the interaction.** We predefine ten common feedback categories, including issues related to syntax and formatting, efficiency, functionality, clarity, bugs, security, compatibility, resource use, scalability, and best practices, with each category detailed in Appendix B. GPT-4 is then prompted to select the most relevant feedback for the scenario and generate appropriate responses within that feedback category. By incorporating this simulated feedback into the dialogue history, GPT-4 is encouraged to refine its solutions further, mimicking intricate user-model exchanges and demonstrating self-correction in response to human input. Through this simulation approach, we have constructed 51K examples, effectively cap-
turing the nuanced dynamics of user interactions and feedback-driven solution refinement.

**Code Correction.** To boost the model’s error-handling capabilities, we include a focused stage in our data compilation that generates 500 specific error correction interactions. We initiate this by prompting GPT-4 to intentionally produce incorrect code snippets, as outlined in Appendix B. The model then uses the error messages from executing these snippets as cues for corrections. This approach mirrors the real-life coding cycle, where developers continuously debug and refine their code, thus enriching our dataset with a broad spectrum of error correction examples. Following this, we replace the initial prompts that resulted in incorrect code with the ones that encourage the generation of correct code outputs. This method ensures the model learns from both successful code generation and error identification and correction, significantly enhancing its problem-solving skills and understanding of the debugging process.

### 2.2 Coding Challenges from LeetCode

**LeetCode Similar Problem.** Drawing inspiration from the practice among programmers of honing their skills through LeetCode challenges, we gather similar LeetCode questions and their solutions from the TACO dataset (Li et al., 2023b). LeetCode categorizes related questions through tags, facilitating the extraction of connected problems. TACO ensures the LeetCode dataset is cleansed to prevent any unintended impact on other task datasets, such as HumanEval and MBPP. By amalgamating associated LeetCode questions, we compile 303 multi-turn instances, enriching the dataset with varied coding challenges.

**LeetCode Follow-up Question.** We further delve into the LeetCode dataset to isolate solutions to identical questions that differ in time or space complexity or are implemented in various programming languages. This process of aggregating diverse solutions to the same LeetCode questions yields 200 multi-round instances, showcasing alternative problem-solving approaches.

Given the original LeetCode solutions often lack comprehensive natural language explanations, we engage GPT-4 to enhance these solutions with integrated text explanations and code snippets, standardizing all instances into a consistent format. The specific prompts used to guide GPT-4 in this enrichment process are detailed in Appendix C, ensuring clarity and educational value in the responses.

### 3 Experimental Setup

**Training Setup.** We select two capable base models CodeLlama (Roziere et al., 2023) and DeepSeekCoder (Guo et al., 2024) varying capacities to illustrate the dataset’s universal applicability and benefits across different scales (7B, 13B, 34B, 70B). We maintain uniform hyperparameter configurations across all models. We fine-tune the base models for 3 epochs. The learning rate is set as 2e-5 with a 0.05 warm-up ratio and a cosine scheduler. We impose a token cutoff length of 4096 to maintain consistency in the input size.

To optimize the fine-tuning process, we strategically combine high-quality single-turn data from the WizardCoder 110k dataset with our CodeFeedback at a ratio of 2:1. Blending with single-turn high-quality data may further boost the coding ability. This blend is carefully selected and more details are discussed in Table 2.

**Evaluation Setup.** Our evaluation framework primarily leverages HumanEval (Chen et al., 2021) and MBPP (Austin et al., 2021), two benchmarks renowned for their rigorous testing of code generation capabilities. Acknowledging the limitations of their original test suites in covering all edge cases (Liu et al., 2023), we further incorporate their extended versions, HumanEval+ and MBPP+, utilizing the EvalPlus framework (Liu et al., 2023) for a more comprehensive assessment.

In line with best practices outlined in recent studies (Liu et al., 2023; Chen et al., 2023), OpenCodeInterpreter’s solutions are generated via greedy decoding. For comparisons involving GPT-3.5 Turbo (OpenAI, 2022) and GPT-4 Turbo (OpenAI, 2023), we maintain a temperature setting of 0. EvalPlus’s unified sanitizer tool post-processes these solutions, which are then evaluated across the four benchmarks using EvalPlus’s toolset.

For single-turn code generation, we craft a simple instruction to encapsulate the original prompt, forming a new input for the model. The exact prompts are detailed in Appendix D, and we assess the model’s performance using the pass@1 metric, as per EvalPlus’s guidelines.

Our analysis extends to multi-turn pass rates to explore OpenCodeInterpreter’s proficiency in refining code through iterative feedback. This aspect of the evaluation draws on execution results...
<table>
<thead>
<tr>
<th>Model</th>
<th>Size</th>
<th>Type</th>
<th>Open-source Model</th>
<th>Data</th>
<th>HumanEval (+)</th>
<th>MBPP (+)</th>
<th>Average (+)</th>
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<tbody>
<tr>
<td>GPT-4 Turbo</td>
<td>-</td>
<td>-</td>
<td>o</td>
<td>o</td>
<td>85.4 (81.7)</td>
<td>83.0 (70.7)</td>
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<td></td>
<td></td>
<td>88.0 (84.2)</td>
<td>92.0 (78.2)</td>
<td>90.0 (81.2)</td>
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<tr>
<td>GPT-3 Turbo</td>
<td>-</td>
<td>-</td>
<td>o</td>
<td>o</td>
<td>72.6 (65.9)</td>
<td>81.7 (69.4)</td>
<td>77.2 (67.7)</td>
</tr>
<tr>
<td>+ Execution Feedback</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>76.8 (70.7)</td>
<td>87.0 (73.9)</td>
<td>81.9 (72.3)</td>
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<tr>
<td>Gemini Pro (Google et al., 2023)</td>
<td>-</td>
<td>-</td>
<td>o</td>
<td>o</td>
<td>63.4 (55.5)</td>
<td>72.9 (57.9)</td>
<td>68.2 (56.7)</td>
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</table>

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<thead>
<tr>
<th>Model</th>
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<th>Open-source Model</th>
<th>Data</th>
<th>HumanEval (+)</th>
<th>MBPP (+)</th>
<th>Average (+)</th>
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<td>Base</td>
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<td>29.3 (25.6)</td>
<td>49.9 (42.1)</td>
<td>39.6 (33.9)</td>
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<tr>
<td>OpenChat (Wang et al., 2023a)</td>
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<td>Instruct</td>
<td>•</td>
<td>•</td>
<td>72.0 (67.1)</td>
<td>62.7 (52.9)</td>
<td>67.4 (60.0)</td>
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<td>Base</td>
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<td>67.8 (60.0)</td>
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<tr>
<td>+ Execution Feedback</td>
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<td></td>
<td></td>
<td></td>
<td>75.6 (69.5)</td>
<td>66.9 (55.4)</td>
<td>71.3 (62.5)</td>
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<td>37.8 (34.1)</td>
<td>57.6 (45.4)</td>
<td>47.7 (39.8)</td>
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<tr>
<td>WizardCoder-CL (Luo et al., 2023)</td>
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<td>Instruct</td>
<td>o</td>
<td>o</td>
<td>48.2 (40.9)</td>
<td>56.6 (47.1)</td>
<td>52.4 (44.0)</td>
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<td>Magicoder-CL (Wei et al., 2023)</td>
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<td>Instruct</td>
<td>•</td>
<td>•</td>
<td>60.4 (55.5)</td>
<td>64.2 (52.6)</td>
<td>62.3 (54.1)</td>
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<tr>
<td>Magicoder-S-CL (Wei et al., 2023)</td>
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<td>Instruct</td>
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<td>•</td>
<td>70.7 (65.6)</td>
<td>68.4 (56.6)</td>
<td>69.6 (61.6)</td>
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<td>72.6 (67.7)</td>
<td>66.8 (55.4)</td>
<td>69.5 (61.6)</td>
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<td>+ Execution Feedback</td>
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<td></td>
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<td>75.6 (70.1)</td>
<td>69.9 (60.7)</td>
<td>72.8 (65.9)</td>
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<td>DeepSeekCoder (Guo et al., 2024)</td>
<td>6.7B</td>
<td>Base</td>
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<td>•</td>
<td>47.6 (39.6)</td>
<td>70.2 (56.6)</td>
<td>58.9 (48.1)</td>
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<tr>
<td>DeepSeekCoder-Instruct</td>
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<td>•</td>
<td>•</td>
<td>73.8 (70.1)</td>
<td>73.2 (63.4)</td>
<td>76.0 (69.8)</td>
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<tr>
<td>+ Execution Feedback</td>
<td></td>
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<td></td>
<td>80.5 (75.6)</td>
<td>79.9 (70.4)</td>
<td>80.2 (73.0)</td>
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<td>66.5 (60.4)</td>
<td>75.4 (61.9)</td>
<td>71.0 (61.2)</td>
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<td>Magicoder-S-DS (Wei et al., 2023)</td>
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<td>76.8 (70.7)</td>
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<td>+ Execution Feedback</td>
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<td>OpenCodeInterpreter-DS</td>
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<tr>
<td>+ Synth. Human Feedback</td>
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<td>87.2 (86.6)</td>
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<td>+ Synth. Human Feedback (Oracle)</td>
<td>6.7B</td>
<td>Instruct</td>
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<td>89.7 (86.6)</td>
<td>87.2 (75.2)</td>
<td>88.5 (80.9)</td>
</tr>
</tbody>
</table>

Table 1: Pass@1 accuracy of different code models on HumanEval (+), MBPP (+) and their average (+). ‘CL’: based on CodeLlama; ‘DS’: based on DeepseekCoder. Baseline results are copied from the EvalPlus Leaderboard or replicated by running the official checkpoints. We highlight strong baselines and our methods for each scale.
and synthetic human feedback, generated by GPT-4 (OpenAI, 2023), to simulate real-world coding scenarios and interactions. Specifically, the multi-turn evaluation encompasses three scenarios, offering a holistic view of OpenCodeInterpreter’s capabilities in dynamic code refinement:

- **Execution Feedback**: Here, OpenCodeInterpreter independently leverages execution outcomes and compiler diagnostics to pinpoint and correct errors, mirroring a developer’s process of refining code based on direct execution feedback.
- **Synthetic Human Feedback**: In this scenario, GPT-4 generates feedback that mimics human input by considering the task description, initial model response, and any execution feedback. This tests OpenCodeInterpreter’s adaptability to nuanced, human-like feedback, reflecting real-world developer or user interactions.
- **Synthetic Human Feedback (Oracle)**: Building on the previous scenario, GPT-4 also accesses the ground-truth solution, offering insight into OpenCodeInterpreter’s optimal performance in code refinement when guided by precise feedback.

For each task, the code generation and evaluation process concludes either when the model’s solution successfully passes the evaluation or when it reaches the set maximum of two rounds. If a code sample fails the evaluation, both the solution and the test results are reincorporated into the prompt for refinement. The evaluation identifies three principal scenarios for non-passing outcomes: 1) **Exception Handling**: Captures and relays any exceptions or errors encountered during execution as error messages, providing direct feedback for correction. 2) **Not-Expected**: In instances where outputs deviate from expected results, the model receives feedback including test inputs, expected outputs, and actual outputs, highlighting the discrepancy. 3) **Timeout Handling**: Implements a timeout threshold to prevent evaluation delays from solutions with excessive or infinite runtimes. Exceeding this threshold triggers an “Execution timed out” notification.

4 Main Results

This section reports OpenCodeInterpreter and baselines in single-turn and multi-turn code generation settings. The results are in Table 1.

4.1 Results of Single-turn Code Generation

We compare OpenCodeInterpreter’s single-turn code generation performance against premier models such as GPT-3.5/4-Turbo (OpenAI, 2022, 2023), CodeLlama-Python (Roziere et al., 2023), Wizard-Coder (Luo et al., 2023), Deepseek-Coder (Guo et al., 2024), CodeT5+ (Wang et al., 2023c) across different scales. Leveraging data from the EvalPlus leaderboard as of February 10th, 2024, we examine OpenCodeInterpreter’s achievements on the HumanEval and MBPP benchmarks, as well as their advanced versions, HumanEval+ and MBPP+. For straightforward comparisons, we consolidate results across different model scales into one table, facilitating direct performance comparisons between each model scale and the respective variants of OpenCodeInterpreter.

Our experimental analysis reveals OpenCodeInterpreter’s strong performance, with several configurations matching or surpassing leading benchmarks. The OpenCodeInterpreter-DS 33B variant achieves the highest scores among open-source models. This accomplishment is remarkable, especially considering the significant presence of low-quality or incorrect data in the initial training set.

4.2 Results of Multi-turn Code Generation

This section evaluates the proficiency of OpenCodeInterpreter in multi-turn interactions through iterative refinement, leveraging interpreter diagnostics and human insights.

Our experimental evaluation imposes a two-round limit on iterations to maintain fairness and consistency across tasks. While some issues may benefit from multiple refinements, others require fewer. This limitation offers clear insights into the model’s iterative capabilities. In the execution feedback scenario, our models across all scales exhibited superiority over state-of-the-art (SOTA) benchmarks, with the OpenCodeInterpreter 33B model achieving parity with GPT-4 Turbo’s single-round score, thus establishing a new SOTA benchmark among the evaluated code models.

Due to budget constraints, our Human Feedback and Human Feedback (Oracle) assessments concentrate on the OpenCodeInterpreter 6.7B and OpenCodeInterpreter 33B models. The outcomes reveal that with Human Feedback, the OpenCodeInterpreter 6.7B model significantly outperformed GPT-4 Turbo’s single-round score, while in the Human Feedback (Oracle) scenario, the OpenCodeIn-
DeepSeekCoder-Base-33B.

Our findings are illustrated in Table 2. It shows that incorporating high-quality single-turn data (e.g., WizardCoder dataset) significantly improves our model’s multi-turn performance. This strategic incorporation ensures that the model benefits from the syntactic accuracy and logical coherence inherent in single-turn tasks, thereby enriching its capacity for nuanced, iterative refinement in subsequent turns. It reveals the critical role of high-quality single-turn inputs in setting the stage for more effective multi-turn code generation and refinement.

Benefits of Diverse Multi-Turn Data Sources. Following the enhanced baseline established by fully integrating the WizardCoder dataset, this subsection investigates the advantages of different data sources on the model’s refinement and debugging efficacy. We add diverse data sources to our training regimen, including Single-turn Packing, Interaction Simulation, and Code Correction Data, both individually and in combination.

The use of these multi-turn data sources, including Single-turn Packing, Interaction Simulation, and Code Correction Data, individually and in combination, demonstrably enhances OpenCodeInterpreter’s debugging and refinement functions. Notably, the inclusion of Code Correction Data significantly elevates the model’s efficiency in correcting errors. This underscores the profound impact of a varied and targeted training approach on advancing the capabilities of sophisticated code generation models. Such an approach enables these models to more effectively address complex coding challenges, correct errors, and refine outputs via extensive feedback mechanisms.

### 4.3 Ablations of Data Sources

This section systematically explores the impact of various data sources on the performance of OpenCodeInterpreter. We conduct a series of ablation studies to evaluate the influence of high-quality single-turn data and diverse multi-turn feedback mechanisms on the model’s code generation, debugging, and refinement capabilities.

#### Impact of High-Quality Single-Turn Data.

To evaluate the effect of high-quality single-turn data on OpenCodeInterpreter’s efficacy, we incorporate the WizardCoder 110K dataset, renowned for its syntactic accuracy and logical coherence, into our extensive multi-turn dataset. This integration seeks to identify the optimal mix of precise, single-turn code generation and the advanced, iterative refinement enabled by multi-turn interactions.

Our experiments employ a soft-target fine-tuning strategy across six configurations, varying the proportion of WizardCoder 110K data in our multi-turn dataset. These configurations span from full incorporation to total exclusion of the WizardCoder dataset, assessing the performance of the model in two versions: DeepSeekCoder-Base-6.7B and DeepSeekCoder-Base-33B.

Our findings are illustrated in Table 2. It shows that incorporating high-quality single-turn data (e.g., WizardCoder dataset) significantly improves our model’s multi-turn performance. This strategic incorporation ensures that the model benefits from the syntactic accuracy and logical coherence inherent in single-turn tasks, thereby enriching its capacity for nuanced, iterative refinement in subsequent turns. It reveals the critical role of high-quality single-turn inputs in setting the stage for more effective multi-turn code generation and refinement.

#### Benefits of Diverse Multi-Turn Data Sources.

Following the enhanced baseline established by fully integrating the WizardCoder dataset, this subsection investigates the advantages of different data sources on the model’s refinement and debugging efficacy. We add diverse data sources to our training regimen, including Single-turn Packing, Interaction Simulation, and Code Correction Data, both individually and in combination.

The use of these multi-turn data sources, including Single-turn Packing, Interaction Simulation, and Code Correction Data, individually and in combination, demonstrably enhances OpenCodeInterpreter’s debugging and refinement functions. Notably, the inclusion of Code Correction Data significantly elevates the model’s efficiency in correcting errors. This underscores the profound impact of a varied and targeted training approach on advancing the capabilities of sophisticated code generation models. Such an approach enables these models to more effectively address complex coding challenges, correct errors, and refine outputs via extensive feedback mechanisms.

### Table 2: Performance of OpenCodeInterpreter with data mixed ratios of single-turn data and Code-Feedback. “E.F” indicates the use of execution feedback.

<table>
<thead>
<tr>
<th>Ratio</th>
<th>E.F</th>
<th>HumanEval (+)</th>
<th>MBPP (+)</th>
<th>Average (+)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0:1</td>
<td>✔</td>
<td>76.2 (71.3)</td>
<td>66.7 (76.6)</td>
<td>71.5 (74.0)</td>
</tr>
<tr>
<td>1:5</td>
<td>✔</td>
<td>70.7 (67.0)</td>
<td>73.4 (63.1)</td>
<td>72.1 (65.1)</td>
</tr>
<tr>
<td></td>
<td>✔</td>
<td>75.6 (70.7)</td>
<td>79.2 (67.9)</td>
<td>77.4 (69.3)</td>
</tr>
<tr>
<td>1:3</td>
<td>✔</td>
<td>76.2 (72.0)</td>
<td>75.4 (65.4)</td>
<td>75.8 (68.7)</td>
</tr>
<tr>
<td></td>
<td>✔</td>
<td>78.0 (75.0)</td>
<td>79.2 (69.9)</td>
<td>78.6 (72.5)</td>
</tr>
<tr>
<td>1:1</td>
<td>✔</td>
<td>75.7 (71.9)</td>
<td>72.9 (62.9)</td>
<td>74.3 (67.4)</td>
</tr>
<tr>
<td></td>
<td>✔</td>
<td>78.7 (75.6)</td>
<td>77.9 (65.9)</td>
<td>78.3 (70.8)</td>
</tr>
<tr>
<td>2:1</td>
<td>✔</td>
<td>75.4 (62.9)</td>
<td>74.6 (62.6)</td>
<td>76.0 (67.6)</td>
</tr>
<tr>
<td></td>
<td>✔</td>
<td>78.0 (72.6)</td>
<td>78.4 (65.9)</td>
<td>78.2 (69.3)</td>
</tr>
<tr>
<td></td>
<td>☒</td>
<td>76.2 (71.3)</td>
<td>66.7 (65.9)</td>
<td>75.1 (67.9)</td>
</tr>
<tr>
<td></td>
<td>☒</td>
<td>75.7 (71.9)</td>
<td>72.9 (62.9)</td>
<td>74.3 (67.4)</td>
</tr>
<tr>
<td></td>
<td>☒</td>
<td>78.7 (75.6)</td>
<td>77.9 (65.9)</td>
<td>78.3 (70.8)</td>
</tr>
<tr>
<td></td>
<td>☒</td>
<td>75.4 (62.9)</td>
<td>74.6 (62.6)</td>
<td>76.0 (67.6)</td>
</tr>
<tr>
<td></td>
<td>☒</td>
<td>78.0 (72.6)</td>
<td>78.4 (65.9)</td>
<td>78.2 (69.3)</td>
</tr>
<tr>
<td></td>
<td>☒</td>
<td>76.2 (71.3)</td>
<td>66.7 (65.9)</td>
<td>75.1 (67.9)</td>
</tr>
</tbody>
</table>

### Table 3: Performance comparison of the model across different settings with incremental data source integration. “E.F” indicates the use of execution feedback.

<table>
<thead>
<tr>
<th>Datasets</th>
<th>E.F</th>
<th>Average (+)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-turn Packing</td>
<td>☒</td>
<td>75.0 (66.9)</td>
</tr>
<tr>
<td>Interaction Simulation</td>
<td>✗</td>
<td>75.1 (66.9)</td>
</tr>
<tr>
<td>Single-turn Packing + Interaction Simulation</td>
<td>✗</td>
<td>78.2 (70.1)</td>
</tr>
<tr>
<td>Single-turn Packing + Interaction Simulation + Code Correction</td>
<td>✗</td>
<td>75.2 (65.4)</td>
</tr>
<tr>
<td>Code-Feedback (Full)</td>
<td>✗</td>
<td>78.2 (70.1)</td>
</tr>
</tbody>
</table>

Our findings are illustrated in Table 2. It shows that incorporating high-quality single-turn data (e.g., WizardCoder dataset) significantly improves our model’s multi-turn performance. This strategic incorporation ensures that the model benefits from the syntactic accuracy and logical coherence inherent in single-turn tasks, thereby enriching its capacity for nuanced, iterative refinement in subsequent turns. It reveals the critical role of high-quality single-turn inputs in setting the stage for more effective multi-turn code generation and refinement.
4.4 Analysis of Dataset Leakage

We conduct a thorough analysis to address dataset leakage, aiming to assess the degree of overlap between our proposed Code-Feedback dataset and the benchmarks utilized in our study, namely HumanEval (+) and MBPP (+).

We specifically examine the duplication ratio of code snippets between our dataset and the benchmarks (Chen et al., 2021), focusing on consecutive lines to gauge the extent of similarity. The results of our analysis are summarized in the table below. As depicted in Table 4, the duplicate line ratios are notably low across all examined consecutive line lengths. This indicates minimal overlap between our dataset and the benchmarks, thereby mitigating concerns regarding dataset leakage.

<table>
<thead>
<tr>
<th>Consecutive Lines</th>
<th>HumanEval (+)</th>
<th>MBPP (+)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 lines</td>
<td>1.19%</td>
<td>0.51%</td>
</tr>
<tr>
<td>6 lines</td>
<td>0.53%</td>
<td>0.00%</td>
</tr>
<tr>
<td>7 lines</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

Table 4: Duplicate Line Ratios between Code-Feedback Dataset and Code Benchmarks.

Furthermore, upon closer examination of the duplicated lines, we observe that the majority are generic and widely used code snippets. These snippets contribute minimally to the performance improvement on specific benchmarks, as they are not indicative of dataset-specific patterns or characteristics. In light of these findings, we can confidently assert that the risk of dataset leakage is low, affirming the integrity and independence of our Code-Feedback dataset.

4.5 Evaluation of Multi-turn Settings

To address the need for a challenging multi-turn evaluation dataset beyond HumanEval and MBPP, we conduct tests on coding-type questions in the MT-Bench (Zheng et al., 2024) dataset, which comprises 10 coding-type questions, each including a primary question and a follow-up question. We follow the standard MT-Bench setup and utilize GPT-4 to score the model outputs (from 1-10). The test results are presented in the table below.

The analysis of the performance of OpenCodeInterpreter in the MT-Bench dataset reveals that OpenCodeInterpreter-DS-33B and OpenCodeInterpreter-DS-6.7B tend to perform better compared to other open-source models. Notably, when compared with DeepSeek-Coder-33B, OpenCodeInterpreter-DS-33B and OpenCodeInterpreter-DS-6.7B show improved performance in the second turn, further demonstrating the usefulness of our Code-Feedback dataset.

<table>
<thead>
<tr>
<th>Model</th>
<th>First Turn</th>
<th>Second Turn</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPT-4</td>
<td>9.0</td>
<td>8.1</td>
<td>8.6</td>
</tr>
<tr>
<td>GPT-3.5-Turbo</td>
<td>6.6</td>
<td>7.2</td>
<td>6.9</td>
</tr>
<tr>
<td>Claude-Instant-V1</td>
<td>6.5</td>
<td>7.0</td>
<td>6.8</td>
</tr>
<tr>
<td>OpenCI-DS-33B</td>
<td>6.8</td>
<td>6.7</td>
<td>6.8</td>
</tr>
<tr>
<td>OpenCI-DS-6.7B</td>
<td>6.7</td>
<td>5.8</td>
<td>6.3</td>
</tr>
<tr>
<td>DS-33B-Instruct</td>
<td>6.7</td>
<td>4.2</td>
<td>5.5</td>
</tr>
<tr>
<td>DS-6.7B-Instruct</td>
<td>5.6</td>
<td>4.5</td>
<td>5.1</td>
</tr>
<tr>
<td>OpenCI-CL-34B</td>
<td>5.6</td>
<td>4.1</td>
<td>4.9</td>
</tr>
<tr>
<td>OpenCI-CL-70B</td>
<td>5.7</td>
<td>3.7</td>
<td>4.7</td>
</tr>
<tr>
<td>OpenCI-CL-13B</td>
<td>5.5</td>
<td>3.7</td>
<td>4.6</td>
</tr>
<tr>
<td>CL-34B-Instruct</td>
<td>4.5</td>
<td>3.4</td>
<td>4.0</td>
</tr>
<tr>
<td>Vicuna-33B-V1.3</td>
<td>3.8</td>
<td>2.9</td>
<td>3.4</td>
</tr>
<tr>
<td>Vicuna-13B-V1.3</td>
<td>3.8</td>
<td>2.7</td>
<td>3.3</td>
</tr>
<tr>
<td>CL-7B-Instruct</td>
<td>3.3</td>
<td>2.5</td>
<td>2.9</td>
</tr>
<tr>
<td>CL-13B-Instruct</td>
<td>3.3</td>
<td>2.3</td>
<td>2.8</td>
</tr>
</tbody>
</table>

Table 5: Performance of various models on the 10 code-related questions in the MT-Bench dataset. ‘CL’ : based on CodeLlama; ‘DS’ : based on DeepSeekCoder

4.6 Case Study: Coding Queries in the Wild

This section delves into three distinct case studies to demonstrate OpenCodeInterpreter’s operational dynamics when faced with “wild” user queries. The motivation behind these case studies is to showcase the practical applications of OpenCodeInterpreter.

In a notable success story (Figure A8), we tasked OpenCodeInterpreter with developing a function to calculate all prime numbers within the 1-100 range, later extending the solution to any arbitrary range x-y. Another commendable instance (Figure A9) involved OpenCodeInterpreter implementing a Python function to validate IPv6 addresses using regular expressions. Demonstrating its capability to iteratively refine its approach, OpenCodeInterpreter not only identified and corrected errors but also enhanced the solution based on human feedback. These two cases exemplify OpenCodeInterpreter’s strength in understanding mathematical logic and dynamically adjusting algorithms to meet specified criteria.

A challenging case (Figure A10) arose when OpenCodeInterpreter was asked to design a function identifying the intersection of two input lists, returning tuples of distinct elements present in both lists alongside their occurrence frequencies. Despite OpenCodeInterpreter’s attempts at correction, it addressed errors incrementally, ultimately exceeding the maximum number of attempts (three). This case sheds light on OpenCodeInterpreter’s
limitations in simultaneously tackling multiple challenging errors.

Through these case studies, we gain invaluable insights into OpenCodeInterpreter’s capabilities and limitations. These insights are crucial for guiding future enhancements to OpenCodeInterpreter.

5 Related Work

LLMs for Code. It becomes a common practice to include code data for pre-training LLMs. For example, 5% of PaLM’s (Chowdhery et al., 2023) pre-training data is code, and this ratio for LaMDA (Thoppilan et al., 2022), Galactica (Taylor et al., 2022), LLaMA (Touvron et al., 2023), Gopher (Rae et al., 2021), GPT-NeoX (Black et al., 2022) is 13%, 7%, 5%, 3%, and 8%, respectively.

Additionally, specialized LLMs have been pre-trained for generating code, e.g., CodeGen (Nijkamp et al., 2022), PanGu-Coder (Christopoulou et al., 2022), CodeGeeX (Zheng et al., 2023), CodeFuse (Di et al., 2023), CodeT5+ (Wang et al., 2023d), AlphaCode (Li et al., 2022), InCoder (Fried et al., 2022), StarCoder (Li et al., 2023a), DeepSeek-Coder (Guo et al., 2024). On the other hand, code LLMs can be fine-tuned from general-purpose LLMs, e.g., CodeLlama (Roziere et al., 2023), WizardCoder (Luo et al., 2023), which is the approach we take here. Compared to specialized LLMs, the fine-tuning paradigm enables us to explore ways to improve code generation capabilities by leveraging pre-trained general-purpose LLMs, especially because these LLMs have already been trained on an extensive amount of code data.

Iterative Code Generation and Refinement. For many sequence generation tasks, iterative approaches are often taken to improve the generation quality, e.g., script generation (Tandon et al., 2021), summarization (Scheurer et al., 2022), and other tasks as shown in (Madaan et al., 2022; Saunders et al., 2022). Notably, in Self-Refine (Madaan et al., 2023), an LLM generates feedback after generating initial outputs, and the LLM iteratively updates the outputs with the feedback. Whereas it focuses on a general-purpose LLM setting, we focus on code generation tasks. As for code generation with LLMs, DebugBench (Tian et al., 2024) observes that incorporating runtime feedback improves code LLMs’ debugging performance. A most recent and relevant work is StepCoder (Dou et al., 2024), where, following the paradigm of relying on reinforcement learning with compiler feedback (Le et al., 2022; Shojaee et al., 2023), the authors further divide the original exploration problems into a sequence of easier sub-tasks. However, our approach does not rely on reinforcement learning and has access to the intermediate generation, which makes the training easier and more stable.

6 Conclusion

In conclusion, OpenCodeInterpreter represents a significant leap forward in the field of code generation, bridging the previously identified gap between open-source models and the advanced capabilities of proprietary systems like the GPT-4 Code Interpreter. By integrating compiler diagnostics and human feedback into an iterative refinement process, OpenCodeInterpreter not only surpasses traditional one-off generation approaches but also introduces a level of adaptability and precision previously unseen in open-source models. The introduction of Code-Feedback, with its extensive multi-turn interactions, further empowers OpenCodeInterpreter to dynamically refine code in response to evolving user intents and complex coding tasks.

Ethics Statement

The development and deployment of OpenCodeInterpreter, alongside the use of Code-Feedback, take ethical considerations to ensure responsible usage. We have made efforts to ensure that the dataset represents a diverse range of coding styles, problem domains, and user scenarios to prevent the propagation of biased or unfair outcomes. Given that OpenCodeInterpreter can generate and refine code based on user inputs, we strictly check out the dataset to ensure that it does not expose sensitive information or create security vulnerabilities. OpenCodeInterpreter has the potential to democratize coding by lowering the barrier to entry for non-experts and developers. We open-source all our code, models, and datasets to maximize accessibility.

Limitations

While OpenCodeInterpreter introduces significant advancements in automated code generation, it is important to acknowledge the limitations inherent in the system and the Code-Feedback that supports it. Although OpenCodeInterpreter is designed to support multi-language code generation and understand a wide range of programming contexts, its performance may vary across different languages and specific domains. While OpenCodeInterpreter
excels at interpreting and responding to a variety of coding tasks, it may struggle with extremely complex or ambiguous user intents. The ability to accurately capture and address such intents is limited by the model’s current understanding and the specificity of the data in Code-Feedback.

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A Source Data Filtering

Here, we outline the prompts used for source data filtering.

### Query Filtering Prompt 1

Rate the following code queries on a scale of 1 to 5 based on their complexity, where 1 is the easiest and 5 is the most difficult. Consider the complexity of the query.

**Query:** 
{{\{query\}}}

You are obliged to choose only from the following list.

**Scoring Criteria:**
1 Point - Very Basic: The query involves simple operations or common issues
2 Points - Basic: The query involves fundamental programming concepts or commonly used functions
3 Points - Intermediate: The query requires some programming experience, possibly involving multiple steps
4 Points - Difficult: The query involves advanced programming skills, including complex logic, algorithms, or data structures
5 Points - Very Difficult: The query requires extensive expertise, potentially involving innovative problem-solving approaches or unique algorithm design

Please give the score first then explain why.

### Query Filtering Prompt 2

Rate the following code queries on a scale of 1 to 5 based on their complexity, where 1 is the easiest and 5 is the most difficult. Consider the complexity of the query.

**Query:** {{\{query\}}}

You are obliged to choose only from the following list.

**Scoring Criteria:**
1 Point - Moderately Difficult: Involves understanding specific programming concepts or libraries, and may include medium complexity algorithms or data structures like basic sorting algorithms or tree structures.
2 Points - Challenging: Requires handling more complex logic or algorithms such as advanced sorting algorithms, recursive logic, or intermediate data structures like hash tables and heaps.
3 Points - Highly Challenging: Demands deeper knowledge in algorithms and data structures, potentially including graph algorithms, dynamic programming, or complex string manipulation techniques.
4 Points - Advanced: Focuses on proficiency in programming and algorithm design, dealing with complex system architecture issues, performance optimization, or solving advanced algorithmic challenges like NP-hard problems.
5 Points - Expert Level: The highest difficulty level, requiring innovative problem-solving approaches or unique algorithm design, possibly involving interdisciplinary knowledge or the application of cutting-edge technologies.

Please give the score first then explain why.
Below is an overview of the data filtering process applied to the initial seed dataset, with Figure A1 summarizing the data quantity after each filtering stage.

![Figure A1: Overview of Data Filtering Process and Corresponding Data Quantities](image)

The pie chart in Figure A2 illustrates the distribution of programming languages in our dataset after filtering.

![Figure A2: Distribution of Programming Languages in Filtered Dataset](image)
## B Simulating Interactions for Data Collection

We illustrate the prompts used in multi-turn execution feedback and multi-turn human feedback respectively.

### System prompt for multi-turn execution feedback

<table>
<thead>
<tr>
<th>You are an AI code interpreter.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Your goal is to help users do a variety of jobs by executing Python code.</td>
</tr>
<tr>
<td>You should:</td>
</tr>
<tr>
<td>1. Comprehend the user’s requirements carefully &amp; to the letter.</td>
</tr>
<tr>
<td>2. Give a brief description for what you plan to do &amp; call the provided function to run code.</td>
</tr>
<tr>
<td>3. Provide results analysis based on the execution output.</td>
</tr>
<tr>
<td>4. If error occurred, try to fix it.</td>
</tr>
<tr>
<td>5. Response in the same language as the user.</td>
</tr>
</tbody>
</table>

### System prompt for multi-turn human feedback

<table>
<thead>
<tr>
<th>You are a user who gives feedback to the latest generated code. If no available code is found in the conversation, you should give a feedback to encourage assistant to generate code. NOTE: your feedback should be WITHIN 2 SHORT SENTENCES.</th>
</tr>
</thead>
<tbody>
<tr>
<td>You can refer to the following types of feedback:</td>
</tr>
<tr>
<td>1. <strong>Syntax and Formatting</strong>: Checking for syntax errors, inconsistent formatting, and suggesting adherence to standard coding styles for readability and maintainability.</td>
</tr>
<tr>
<td>2. <strong>Efficiency</strong>: Identifying parts of the code that can be optimized for better performance, such as reducing time complexity, optimizing loops, or suggesting more efficient data structures.</td>
</tr>
<tr>
<td>3. <strong>Functionality Enhancements</strong>: Suggesting additional features or enhancements that could make the code more functional or user-friendly.</td>
</tr>
<tr>
<td>4. <strong>Code Clarity and Documentation</strong>: Recommending improvements in code comments and documentation to make the code more understandable and easier to maintain.</td>
</tr>
<tr>
<td>5. <strong>Bug Identification</strong>: Pointing out any potential bugs or logical errors in the code and suggesting ways to fix them.</td>
</tr>
<tr>
<td>6. <strong>Security Improvements</strong>: Highlighting any security vulnerabilities in the code and suggesting best practices to enhance security.</td>
</tr>
<tr>
<td>7. <strong>Compatibility and Testing</strong>: Advising on making the code more compatible with different environments or platforms and suggesting more comprehensive testing scenarios.</td>
</tr>
<tr>
<td>8. <strong>Resource Optimization</strong>: Identifying areas where the code might be using more resources than necessary (like memory or CPU) and suggesting optimizations.</td>
</tr>
<tr>
<td>9. <strong>Scalability</strong>: Providing insights on how the code can be made more scalable to handle larger data sets or more users.</td>
</tr>
<tr>
<td>10. <strong>Adherence to Best Practices</strong>: Ensuring the code follows the best practices specific to the language or framework being used.</td>
</tr>
</tbody>
</table>

Your output MUST be in a json format like this:

```json
{
  "satisfied": "The points that have been achieved in generated code",
  "not_satisfied": "The points that have not yet been achieved in generated code",
  "feedback": "The actual feedback. Your feedback should be WITHIN 2 SHORT SENTENCES. Feedback must come from a point included in 'not_satisfied' field. You can ask the assistant here to generate code if no available code is found in previous conversations."
}
```
System prompt for deliberately generating incorrect code

You are an AI code interpreter.
Your goal is to generate and execute Python code.

Your code MUST contain at least one of the following types of errors:

1. Syntax Error: This type of error occurs when the code violates the grammar rules of the programming language. For example, forgetting to close a parenthesis or a quotation mark, or misspelling a keyword.
2. Logical Error: These errors sneak into your code when there's a misunderstanding of the problem you're solving, leading to incorrect results despite the code running without crashing. For example, calculating the average of a list of numbers by summing them up but forgetting to divide by the count of the numbers.
3. Type Error: This error occurs when an operation is applied to an object of an inappropriate type. For example, attempting to concatenate a string with an integer without converting the integer to a string first.
4. Name Error: This happens when the code attempts to reference a variable or a function name that hasn't been defined. For example, trying to print a variable that hasn't been declared.
5. Timeout Error: This error occurs when your code gets stuck in a loop that never ends, either due to a logic flaw or a condition that never becomes false. In programming, such an error can cause your application to hang indefinitely, consuming resources and potentially leading to a crash if not handled properly. For example, writing a loop that waits for a certain condition to change, but the condition is never updated within the loop.

NOTE:
1. You MUST make mistakes in the generated code!
2. Do not explain the errors within. Just write your thoughts and code as normal.
3. Do not tell me you are writing the wrong code in any form (e.g., in text/code/comments). Just pretend you are writing the correct code and still not recognizing the errors.

C Natural Language Explanations Generation

We use the following prompt to generate explanations for code using GPT-4.

Prompt for generating natural language explanations using GPT-4

Here is a list containing a series of dialogues between a user and a programmer assistant. Following the previous dialogues, the user posed a latest problem. The assistant has now crafted the correct code based on the previous dialogues and the latest problem. Assuming you are this programmer assistant, please add some text before the code. The purpose of this text is to respond to the latest problem and to introduce the code that follows. This text may include: language used in the code, algorithm used in the code, step-by-step implementation overview, and other relevant content. You may use phrases like "The following code", "My code", "My solution", to refer to the @@Code. Your response should ONLY contain the text that you add before the code. Your only task is to write the text, never modify the code or remind me something. Never restate the previous dialogues and the problem.

@@Previous Dialogues
{previous dialogues}

@@Recent Problem:
{recent problem}

Add the text there.
@@Code:
{code}
D Model Evaluation Prompts

For different benchmarks, distinct prompts were employed during the initial turn of solution generation: identical prompts were utilized for HUMANEVAL and HUMANEVAL+, while MBPP and MBPP+ shared a similar prompt. The prompts are illustrated in the below.

<table>
<thead>
<tr>
<th>Prompt for HumanEval and HumanEval+</th>
</tr>
</thead>
<tbody>
<tr>
<td>You are an exceptionally intelligent coding assistant that consistently delivers accurate and reliable responses to user instructions.</td>
</tr>
<tr>
<td>@@ Instruction</td>
</tr>
<tr>
<td>Here is the given code to do completion:</td>
</tr>
<tr>
<td>```{language}</td>
</tr>
<tr>
<td><code>{original prompt}</code></td>
</tr>
<tr>
<td>```</td>
</tr>
<tr>
<td>Please continue to complete the function with <code>{language}</code> programming language. You are not allowed to modify the given code and do the completion only.</td>
</tr>
<tr>
<td>Please return all completed codes in one code block.</td>
</tr>
<tr>
<td>This code block should be in the following format:</td>
</tr>
<tr>
<td>```{language}</td>
</tr>
<tr>
<td># Your codes here</td>
</tr>
<tr>
<td>```</td>
</tr>
<tr>
<td>@@ Response</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Prompt for MBPP and MBPP+</th>
</tr>
</thead>
<tbody>
<tr>
<td>You are an exceptionally intelligent coding assistant that consistently delivers accurate and reliable responses to user instructions.</td>
</tr>
<tr>
<td>@@ Instruction</td>
</tr>
<tr>
<td>Here is the given problem and test examples:</td>
</tr>
<tr>
<td><code>{original prompt}</code></td>
</tr>
<tr>
<td>Please use the <code>{language}</code> programming language to solve this problem.</td>
</tr>
<tr>
<td>Please make sure that your code includes the functions from the test samples and that the input and output formats of these functions match the test samples.</td>
</tr>
<tr>
<td>Please return all completed codes in one code block.</td>
</tr>
<tr>
<td>This code block should be in the following format:</td>
</tr>
<tr>
<td>```{language}</td>
</tr>
<tr>
<td># Your codes here</td>
</tr>
<tr>
<td>```</td>
</tr>
<tr>
<td>@@ Response</td>
</tr>
</tbody>
</table>
We employ GPT models to emulate human behavior in generating feedback. The prompts provided to the GPT models are presented as follows.

Prompt for GPT models mimicking human feedback with canonical solution

You are tasked with providing guidance to a programmer who has drafted a code for a programming problem. Your role is to mimic human-like responses and offer suggestions for modifying the code based on the canonical solution and the observed execution results. You should NOT directly revealing contents of the @@Canonical Solution or mentioning terms such as "canonical solution." You should refrain from directly writing code. Begin by thoroughly examining the existing code and its functionality. Compare the @@Existing Code with the @@Canonical Solution provided. Note any discrepancies in logic, approach, or implementation. Analyze the @@Execution Result obtained from running the @@Existing Code. Identify any errors, unexpected behavior, or deviations from the expected output. Consider potential edge cases, optimization opportunities, or alternative approaches based on insights from both the @@Canonical Solution and @@Execution Result. Offer guidance in a clear and understandable manner, explaining the rationale behind each suggestion. Refrain from providing actual code solutions, but instead focus on conceptual modifications or strategies. Provide constructive feedback to help the programmer improve their coding skills. Remember, your role is to simulate human-like guidance and expertise in programming without directly implementing solutions. Please respond in no more than three sentences.

@@Problem
{original prompt}

@@Existing Code
{sanitized code}

@@Execution Result
{execution result}

@@Canonical Solution
{canonical solution}

@@Guidance

Prompt for GPT models mimicking human feedback without canonical solution

You are tasked with providing guidance to a programmer who has drafted a code for a programming problem. Your role is to mimic human-like responses and offer suggestions for modifying the code based on the observed execution results. You should refrain from directly writing code. Begin by thoroughly examining the existing code and its functionality. Analyze the @@Execution Result obtained from running the @@Existing Code. Identify any errors, unexpected behavior, or deviations from the expected output. Consider potential edge cases, optimization opportunities, or alternative approaches based on insights from the @@Execution Result. Offer guidance in a clear and understandable manner, explaining the rationale behind each suggestion. Refrain from providing actual code solutions, but instead focus on conceptual modifications or strategies. Provide constructive feedback to help the programmer improve their coding skills. Remember, your role is to simulate human-like guidance and expertise in programming without directly implementing solutions. Please respond in no more than three sentences.

@@Problem
{original prompt}

@@Existing Code
{sanitized code}

@@Execution Result
{execution result}

@@Guidance
E  Examples of Methods used in Data Collection

Here we listed examples of each method in the data collection process, including similar query packing, human feedback simulation and code correction for coding queries from open-source data (Section 2.1), and similar problem packing and follow-up Q&A for coding challenges from LeetCode (Section 2.2).

User:
You are tasked with creating a Python function that processes a given directory and calculates the total size of all files within it. Additionally, the function should exclude any files with a "torrent" extension from the total size calculation. You are provided with a code snippet that demonstrates the use of the `os` module to join a path and a filename, as well as the use of a custom `Torrent` class to read the total size of files in a torrent file.

Create a function `calculate_directory_size` that takes a directory path as input and returns the total size of all files within the directory, excluding any files with a "torrent" extension.

Example:

```python
Given the directory structure:

```
my_directory
    file1.txt
    file2.jpg
    file3.torrent
```

The function call `calculate_directory_size(my_directory)` should return the total size of `file1.txt` and `file2.jpg` in bytes.

Assistant:
```
import os

def calculate_directory_size(directory_path):
    total_size = 0
    for dirpath, _, filenames in os.walk(directory_path):
        for filename in filenames:
            if not filename.endswith(".torrent"):  # only consider non-torrent files
                file_path = os.path.join(dirpath, filename)
                total_size += os.path.getsize(file_path)
    return total_size
```

The `calculate_directory_size` function uses the `os.walk` method to traverse the directory and its subdirectories, and iterates through the files within each directory. For each file, it checks if the file does not have a "torrent" extension and adds its size to the `total_size`. Finally, the function returns the accumulated `total_size` of all non-torrent files within the directory.

User:
You are tasked with creating a Python script that will search for specific files within a given directory and its subdirectories. Your script should be able to identify files with a particular file extension and return a list of these files. Additionally, the script should be able to handle cases where the specified directory does not exist or is empty.

Write a function `find_files(directory, extension)` that takes in two parameters:

- `directory`: A string representing the directory path to search for files.
- `extension`: A string representing the file extension to search for (e.g., "txt", "csv", "py").

The function should return a list of file paths that have the specified file extension within the given directory and its subdirectories. If the directory does not exist or is empty, the function should return an empty list.

Example:

```python
print(find_files('/path/to/directory', '.txt'))
# Output: ['/path/to/directory/file1.txt', '/path/to/directory/subdirectory/file2.txt']
```

Assistant:
```
import os

def find_files(directory, extension):
    file_list = []
    if os.path.exists(directory):
        for root, dirs, files in os.walk(directory):
            for file in files:
                if file.endswith(extension):
                    file_list.append(os.path.join(root, file))
    return file_list
```

The `find_files` function uses the `os.walk` method to traverse the directory and its subdirectories, and iterates through the files within each directory. For each file, it checks if the file has the specified extension and adds its path to the `file_list`. Finally, the function returns the `file_list` of all files with the specified extension within the given directory.

Figure A3: An example of similar query packing for challenging query pools.
User: Develop a program in Python to implement a Simple Linear Regression model.

## Problem Statement ##
Write a Python program to implement a Simple Linear Regression model to predict the salary of employees based on their years of experience.

## Instructions ##
1. The program should ask the user for the number of data points to be entered.
2. The program should then ask the user to enter the years of experience and the corresponding salary for each data point.
3. The program should calculate the slope and intercept of the regression line using the least squares method.
4. The program should use the calculated slope and intercept to predict the salary for a given number of years of experience entered by the user.
5. The program should display the regression line equation, the predicted salary, and a scatter plot of the data points and the regression line.

## Constraints ##
- The number of data points should be a positive integer.
- The years of experience and salary should be non-negative integers.
- You may assume that the input will be valid and no error checking is required.

Assistant: I have implemented the Python program to implement a Simple Linear Regression model based on the instructions provided. The program calculates the regression line slope and intercept using the least squares method and then predicts the salary for the given number of years of experience.

```python
```
```python
# Importing required libraries
import numpy as np

# Simulating user input
num_points = 5
data_points = [(2, 50000), (5, 80000), (10, 120000), (3, 60000), (8, 100000)]
years_to_predict = 7

# Separating years of experience and salary
X = np.array([x[0] for x in data_points])
Y = np.array([x[1] for x in data_points])

# Calculating the mean of X and y
mean_x = np.mean(X)
mean_y = np.mean(Y)

# Calculating the terms needed for the num and den of formula of slope (b1) and intercept (b0)
m = len(X)
umer = 0
denom = 0
for i in range(m):
    numer += (X[i] - mean_x) * (Y[i] - mean_y)
denom += (X[i] - mean_x) ** 2
b1 = numer / denom # slope
b0 = mean_y - (b1 * mean_x) # intercept

# Displaying the regression line equation
print('Regression line equation: y = {:.2f} + {:.2f}x'.format(b0, b1))

# Predicting the salary for the given number of years of experience
predicted_salary = b0 + b1 * years_to_predict

print('Predicted salary for {} years of experience: {:.2f}'.format(years_to_predict, predicted_salary))
```

Execution result:
```
Predicted salary for 7 years of experience: 93893.81
```

The formatted regression line equation is: \(y = 34424.78 + 8495.58x\)

From this equation, the predicted salary for 7 years of experience is: 93893.81

A scatter plot was generated, which visually represents the data points and the predicted regression line. The red points represent the input data points, and the blue line represents the regression line or the salary prediction line.

This plot visually expresses how the model predicts salary based on years of experience. The closer these red points are to the blue line, the better the model is at predicting.

Please let me know if anything else is needed.

User: Consider optimizing the loop for calculating the slope and intercept to enhance code efficiency. Please ensure consistent formatting for better readability.

Assistant: ```python
```
```python
# Python code provided uses the Simple Linear Regression model to predict the salary based on years of experience. The model was trained using 5 data points, each consisting of years of experience and corresponding salary.

The calculated regression line equation from the model is: \(y = 34424.78 + 8495.58x\)

From this equation, the predicted salary for 7 years of experience is: 93893.81

A scatter plot was generated, which visually represents the data points and the predicted regression line. The red points represent the input data points, and the blue line represents the regression line or the salary prediction line.

This plot visually expresses how the model predicts salary based on years of experience. The closer these red points are to the blue line, the better the model is at predicting.

Please let me know if anything else is needed.

User: The Python program has been improved for better code efficiency and readability.

Assistant: The loop for computing the slope (b1) and intercept (b0) of the regression line is eliminated and replaced with an optimized computation using numpy. This change enhances performance, especially when dealing with larger data sets.

The formatted regression line equation is: \(y = 34424.78 + 8495.58x\)

The predicted salary for 7 years of experience is: 93893.81

Please let me know if any further assistance is needed.

Figure A4: An example of human feedback simulation for challenging query pools.
def student_grades(gpvals, prev_gpvals):
    # Correct calculation for lowest and highest GPA values
    lowest_gpa = min(gpvals, key=get_gpa)
    highest_gpa = max(gpvals, key=get_gpa)

    lowest_grade = get_letter(lowest_gpa)
    highest_grade = get_letter(highest_gpa)

    progress = {'improved': 0, 'maintained': 0, 'declined': 0}
    progress['improved'] += 1 if highest_gpa >= 4.5 else progress['maintained']
    progress['declined'] += 1 if highest_gpa < 1.0 else progress['improved']

    # Then, if needed, you can get their corresponding letter grades
    lowest_grade_letter = get_letter(lowest_gpa)
    highest_grade_letter = get_letter(highest_gpa)

    return {'grades': grades, 'average_grade': average_grade, 'lowest_grade': lowest_grade, 'highest_grade': highest_grade, 'progress': progress}

# Example usage:
gpvals = [4.0, 3.0, 1.7, 2.3, 5.0]  
prev_gpvals = [3.5, 3.0, 1.4, 1.8, 3.2]  
student_grades(gpvals, prev_gpvals)
A city's **skyline** is the outer contour of the silhouette formed by all the buildings in that city when viewed from a distance. Given the locations and heights of all the buildings, return _the **skyline** formed by these buildings collectively_.

The geometric information of each building is given in the array `buildings` where `buildings[i] = [left[i], right[i], height[i]]`:

* `left[i]` is the x coordinate of the left edge of the `ith` building.
* `right[i]` is the x coordinate of the right edge of the `ith` building.
* `height[i]` is the height of the `ith` building.

You may assume all buildings are perfect rectangles grounded on an absolutely flat surface at height 0.

The **skyline** should be represented as a list of "key points " coordinate in the form `[x1,y1],[x2,y2],...`. Each key point is the left endpoint of some horizontal segment in the skyline except the last point in the list, which always has a y-coordinate 0 and is used to mark the skyline's termination where the rightmost building ends. Any ground between the leftmost and rightmost buildings should be part of the skyline's contour.

**Note:** There must be no consecutive horizontal lines of equal height in the output skyline. For instance, `[[1,1],[2,3],[4,5],[11,12],[14,14],[17,17],[20,22],[23,23]]` is acceptable; the three lines of height 5 should be merged into one in the final output as such: `[[1,1],[2,3],[4,5],[11,12],[14,17],[20,22],[23,23]]`

**Constraints:**

* `1 <= buildings.length <= 104`
* `0 <= left[i] < right[i] <= 231 - 1`
* `1 <= height[i] <= 231 - 1`

**Examples are truncated**

```python
def getSkyline(buildings):
    points = []
    for L, R, h in buildings:
        points.append((L, -h))
        points.append((R, h))
    points.sort()
    heights = SortedList([0])
    prev = 0
    skyline = []
    for x, cur in points:
        if cur < 0:
            heights.add(-cur)
        else:
            heights.remove(cur)
        cur = heights[-1]
        if cur != prev:
            skyline.append([x, cur])
            prev = cur
    return skyline
```

**Constraints:**

* `1 <= positions.length <= 1000`
* `1 <= left[i] <= 108`
* `1 <= sideLength[i] <= 108`

**Examples are truncated**

```python
from sortedcontainers import SortedList

def getSkyline(buildings):
    points = []
    for L, R, h in buildings:
        points.append((L, -h))
        points.append((R, h))
    points.sort()
    heights = SortedList([0])
    prev = 0
    skyline = []
    for x, cur in points:
        if cur < 0:
            heights.add(-cur)
        else:
            heights.remove(cur)
        cur = heights[-1]
        if cur != prev:
            skyline.append([x, cur])
            prev = cur
    return skyline
e
```

**Assistance:**

In the following code, we tackle the problem of computing a city skyline from a given set of buildings. Each building is defined by its x-coordinate boundaries and height, and our goal is to construct the contour of these buildings when collectively observed from a distance.

The algorithm used can be summarized in the following steps:

**[Steps are truncated]**

My solution is designed to handle the input efficiently and conforms to the problem's constraints regarding sorting and eliminating redundant horizontal lines. Let's proceed with the code that solves the skyline problem.

```python
... python
from sortedcontainers import SortedList

def getSkyline(buildings):
    points = []
    for L, R, h in buildings:
        points.append((L, -h))
        points.append((R, h))
    points.sort()
    heights = SortedList([0])
    prev = 0
    skyline = []
    for x, cur in points:
        if cur < 0:
            heights.add(-cur)
        else:
            heights.remove(cur)
        cur = heights[-1]
        if cur != prev:
            skyline.append([x, cur])
            prev = cur
    return skyline
...
```

Figure A6: An example of similar problem packing for LeetCode problems.
User:
Please solve this problem:
In a galaxy far away, there is a constant battle between the republic and the droid army. The droid army decided to launch their final attack on the republic. They have N space-fighters.

Initially the $S_i$’th space-fighter is located at $(x_{-i}, y_{-i})$. All of the space-fighters move with constant velocity $V$ units/sec in the positive X direction.

i.e., fighter at $(x_{-i}, y_{-i})$ moves to $(x_{-i} + V, y_{-i})$ in 1 second. The $S_i$’th space-fighter broadcasts enemy information at a frequency $f_{S_i}$.

The republic is not scared of the artificially intelligent droid force as they have Yoda. Yoda has a special power, at any time $T$ he can choose a region of the droid army and block one specific frequency $F$.

This power has one constraint; it can be applied only in the form of a two sided unbounded axis parallel rectangular box open towards the both the directions across X axis (refer image below for clarity). If a frequency ($F$) is blocked all the space-fighters in the region having the frequency $F$ can’t communicate.

Given the initial positions of the space-fighters, and their velocity, you are to answer queries of the following form:

YU YD T

where YU, YD are the bounds on y-axis inside which YODA can block a frequency at a time $T$.

In the region described by the query, after a time $T$ seconds from the start, if Yoda can chose one frequency ($F$) he wishes to, what is the maximum number of communications he can block?

Input Format
Each test case is described as follows; the first line contains 3 space separated integers $N$ - the number of space-fighters, $Q$ - the number of queries you have to answer, and $V$ - the velocity of the space-fighters separated by a single space.

$N$ lines follow, each containing 3 space separated integers $x_{-i}$, $y_{-i}$, and $f_{-i}$, denoting the x co-ordinate, y co-ordinate and the frequency at which the $S_i$’th $S_i$ ship broadcasts respectively. Each of the next $Q$ lines contain 3 space separated integers representing YU, YD, T respectively. Refer the figure for more clarity.

Note: Points on the boundaries should be counted as well.

Output Format
For each query you are to output a single integer denoting the result.

Constraints
1 <= $N$ <= 50000
1 <= $Q$ <= 30000
1 <= $V$ <= 10000
$S$-$10^{9}$ $S$ <= $x_{-i}$ <= $S$+$10^{9}$ $S$
$S$-$10^{9}$ $S$ <= $y_{-i}$ <= $S$+$10^{9}$ $S$
1 <= $f_{-i}$ <= $S$+$10^{9}$ $S$
$S$-$10^{9}$ $S$ <= YU <= $S$+$10^{9}$ $S$
$S$-$10^{9}$ $S$ <= YD <= $S$+$10^{9}$ $S$
1 <= $T$ <= 10000
YU >= YD

User: What is the difficulty of this question?

Assistant: The difficulty of the problem described can be considered HARD.

User: Do you have any other way to solve this problem?

Assistant: To provide an alternative solution to the given problem, I’ve utilized the Square Root Decomposition algorithm, which is often used to optimize the computational complexity of problems involving range queries.

[remaining content and generated code are truncated]
F Case Study

User: Write code to calculate all prime numbers in the range of 1-100.

Assistant: Sure, here is a simple Python code to calculate all prime numbers in the range of 1 to 100.

```python
def is_prime(n):
    if n <= 1:
        return False
    elif n <= 3:
        return True
    elif n % 2 == 0 or n % 3 == 0:
        return False
    i = 1
    while i * i <= n:
        if n % i == 0 or n % (i + 2) == 0:
            return False
        i += 1
    return True

for num in range(1, 101):
    if is_prime(num):
        print(num)
```

This code includes a function `is_prime(n)` to check if a number `n` is prime. It then iterates over the numbers 1 to 100 and prints the numbers for which `is_prime(n)` returns `True`.

User: Execution Result:

2
3

Assistant: I apologize for the confusion, there seems to have been an error in the code. The function to check if a number is prime was not correctly implemented. Here is the corrected Python code:

```python
def is_prime(n):
    if n <= 1:
        return False  # numbers less than or equal to 1 are not prime
    elif n <= 3:
        return True  # 2 and 3 are prime
    elif n % 2 == 0 or n % 3 == 0:
        return False  # eliminate multiples of 2 and 3
    i = 5
    while i * i <= n:
        # eliminate multiples of primes already found
        if n % i == 0 or n % (i + 2) == 0:
            return False
        i += 6
    return True
```

User: Execution Result:

53
59
61
67
71
73
79
83
89
97

Assistant: I'm glad to see the code worked as expected! Those are indeed the prime numbers in the range from 50 to 100. If you have any other questions or need further assistance, feel free to ask!

Figure A8: A good case where we required our model to write code to calculate all prime numbers in the range of 1-100, and then generalize the function to arbitrary range x-y. Our model successfully corrected the error and made improvements according to human feedback.
User: Implement a Python function to check if a string is a valid IPv6 address with regular expressions.

Assistant: Sure, here is a Python function using Regular Expression (regex) to check if a string is a valid IPv6 address:

```python
import re
def is_valid_ipv6(s):
    # Checks if a given string is a valid IPv6 address.
    pattern = re.compile(r'^(?:(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)$')
    return bool(pattern.match(s))
```

This function uses a complex regular expression which covers all possible valid IPv6 formats according to RFC 3986. It checks for hexadecimal values which are represented in 8 groups of 4 hexadecimal digits.

Let me know if there's anything else I can assist you with!

User: Can you explain the generated regular expression in detail and make this function more maintainable?

Assistant: I apologize for the confusion. It seems like there was a mistake in the generated explanation for this regular expression and improve its readability with thorough in-line comments.

```python
import re

def is_valid_ipv6(s):
    # Checks if a given string is a valid IPv6 address.
    pattern = re.compile(r'^(?:(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)\.(?:25[0-5]|2[0-4]\d|1\d{2}|[1-9]?\d?)$')
    return bool(pattern.match(s))
```

execute_result:

```
print(is_valid_ipv6("2404:6800:4003:c02::8a"))  # True
print(is_valid_ipv6("102.192.230.21"))            # True
print(is_valid_ipv6("2404:6800:4003:804:200e"))  # False
print(is_valid_ipv6("2404:6800:4003:804:200e"))  # True
```

This function should now correctly validate IPv6 addresses. It should return True for valid IPv6 addresses and False for invalid ones.

User: Execution Result:

```
True
True
False
True
```

Figure A9: A good case that asked our model to implement a Python function to check if a string is a valid IPv6 address with regular expressions. Inspired by errors raised in the execution result, our model managed to recognize the small error from complex regular expression. Then, our model successfully generated explanation for this regular expression and improve its readability with thorough in-line comments.
User:
Design a function that finds the intersection of two input lists, and returns a list of tuples, each containing a distinct element that is present in both lists and its frequency of occurrence. For this task, avoid using Python’s built-in list functions or any libraries to sort the result and remove duplicates. Also, implement your own hash table data structure for this task.

```python
def shared_elements(list1, list2):
    """Return a list of tuples of unique elements that appeared in both lists, but we only want the count per list. Need to adjust this."""
    intersection = []
    hash_map1 = HashMap()  # Own hash table for this task.
    hash_map2 = HashMap()

    for i in range(len(list1)):
        if hash_map1.get(list1[i]) is not None and hash_map2.get(list1[i]) is not None:
            lst = list1[i], hash_map1.get(list1[i]) + hash_map2.get(list1[i])
            intersection.append(lst)

    for i in range(len(list2)):
        if hash_map1.get(list2[i]) is not None and hash_map2.get(list2[i]) is not None:
            lst = list2[i], hash_map1.get(list2[i]) + hash_map2.get(list2[i])
            intersection.append(lst)

    return intersection
```

Assistant: ```python
>>> shared_elements([[1, 4, 1, 3, 4, 653, 2, 5], [5, 7, 1, 5, 9, 653, 121]], [[5, 3, 3, 2, 8], [3, 2]])
[(2, 2), (3, 3)]
```