SEMCODER: Training Code Language Models with Comprehensive Semantics Reasoning

Yangruibo Ding
Columbia University
`yrbding@cs.columbia.edu`

Jinjun Peng
Columbia University
`jinjun@cs.columbia.edu`

Marcus J. Min
Columbia University
`jm5025@columbia.edu`

Gail Kaiser
Columbia University
`kaiser@cs.columbia.edu`

Junfeng Yang
Columbia University
`junfeng@cs.columbia.edu`

Baishakhi Ray
Columbia University
`rayb@cs.columbia.edu`

Abstract

Code Large Language Models (Code LLMs) have excelled at tasks like code completion but often miss deeper semantics such as execution effects and dynamic states. This paper aims to bridge the gap between Code LLMs' reliance on static text data and the need for semantic understanding for complex tasks like debugging and program repair. We introduce a novel strategy, *monologue reasoning*, to train Code LLMs to reason comprehensive semantics, encompassing high-level functional descriptions, local execution effects of individual statements, and overall input/output behavior, thereby linking static code text with dynamic execution states. We begin by collecting PYX, a clean Python corpus of fully executable code samples with functional descriptions and test cases. We propose training Code LLMs not only to write code but also to understand code semantics by reasoning about key properties, constraints, and execution behaviors using natural language, mimicking human verbal debugging, i.e., rubber-duck debugging. This approach led to the development of SEMCODER, a Code LLM with only 6.7B parameters, which shows competitive performance with GPT-3.5-turbo on code generation and execution reasoning tasks. SEMCODER achieves 79.3% on HumanEval (GPT-3.5-turbo: 76.8%), 63.6% on CRUXEval-I (GPT-3.5-turbo: 50.3%), and 63.9% on CRUXEval-O (GPT-3.5-turbo: 59.0%). We also study the effectiveness of SEMCODER's monologue-style execution reasoning compared to concrete scratchpad reasoning, showing that our approach integrates semantics from multiple dimensions more smoothly. Finally, we demonstrate the potential of applying learned semantics to improve Code LLMs' debugging and self-refining capabilities. Our data, code, and models are available at: `https://github.com/ARiSE-Lab/SemCoder`.

1 Introduction

Recent advancements in code language models (Code LMs) [1–5] have revolutionized the field of programming [6–8]. These models, trained primarily on vast corpora of programming-related text such as source code and docstrings [9], excel at automating tasks like code generation.

Unfortunately, the reliance on static text data limits the ability of existing Code LMs to understand what the programs are actually doing, especially to reason about the deeper semantics intrinsic to code execution. The lack of semantic understanding unsurprisingly often leads to poor performance in debugging and repairing errors in generated code [10]. Code LMs struggle with reasoning about program semantics in both static and dynamic settings. In a static setting, the challenge lies in understanding the intended behavior of the code without running it, requiring deep comprehension of

code syntax and static semantic properties (e.g., program dependency graph, etc.) [11, 12]. A dynamic setting involves observing and interpreting the code's behavior during execution, including tracking variable changes, identifying runtime errors, and detecting performance issues [13]. Even when the execution traces are exposed to the model, [13] observed that Code LMs could not effectively interact with the real executions, struggling to leverage the dynamic execution traces for debugging.

Fifty years ago, Terry Winograd envisioned the future AI programmer: "The key to future programming lies in systems which *understand what they are doing* [14]". In this paper, we explore constructing such a programming system, backed up by language models, not only to write programs but also to understand what they are doing (a.k.a., semantics). Our key insight is that Code LMs should mimic how pragmatic human developers work: starting with general specifications, breaking them down into sub-tasks with expected properties and constraints, implementing code line by line while reasoning about the effects of each line, and checking overall correctness by examining execution effects [15]. To achieve this, we introduce a novel strategy to train Code LMs to reason comprehensive program semantics.

We train SEMCODER, a novel semantic-aware Code LM. We incorporate different modalities of program semantics: (i) High-Level Functional Descriptions: We train SEMCODER to understand high-level functional descriptions bi-directionally by both generating code from natural language and summarizing code as natural language. This involves teaching models to grasp a program's purpose, akin to how a human developer outlines software high-level approximate semantics; (ii) Key Properties and Constraints: we train SEMCODER to extract the functional properties and constraints of a program, which should hold for all scenarios and corner cases. (iii) Overall Execution Behavior: we train SEMCODER to understand the local impact of individual code statements, recognizing how each line affects variables, control flow, and memory usage. By grasping these effects, models can better predict code execution semantics. We train the model to learn both abstract and concrete semantics, teaching it the general purpose of a statement and illustrating it with concrete examples.

Curating Executable Code Dataset We collect PYX, a synthetic dataset capturing comprehensive program semantics with executable code samples and unit tests. Inspired by existing datasets [16, 17], we use a powerful LLM to synthesize NL-to-code pairs. To ensure quality, PYX includes only executable samples. It also generates unit tests and detailed execution traces, recording program states after each statement. From PYX, we further construct a debugging dataset, PYX-R. PYX-R includes buggy code snippets generated by Code LMs, corresponding debugging rationales, and refine plans [13] leading to patches. By fine-tuning Code LMs on PYX-R, we aim to develop programming assistants that debug and patch faulty code in a human-like manner, advancing the capabilities of current Code LMs in iterative programming.

Learning Program Semantics To learn program semantics, we propose *monologue reasoning*: Code LMs try to understand and explain the code semantics to themselves. Code LMs will summarize the program functionalities, highlight the key properties and constraints, and reason code execution step-by-step, inspired by rubber duck debugging [15]. The code execution reasoning will be performed in two directions: (i) forward monologue: SEMCODER uses source code and inputs to verbally simulate execution, explaining each line's impact, executed lines, variable changes, and final output, and (ii) backward monologue: given the final output, SEMCODER reasons about possible previous states abstractly, capturing essential characteristics without precise enumeration. This abstract reasoning is crucial for understanding complex operations like sorting or aggregation, where the previous state cannot be uniquely determined. Overall, monologue reasoning equips Code LMs with a human-like understanding of control flow, state transitions, and complex operations, bridging the gap between static code analysis and dynamic execution reasoning.

We show that, by training on this approach, SEMCODER can generate, reason about execution, debug and refine code in a more intuitive and effective manner, pushing the boundaries of what current Code LMs can achieve in different software engineering tasks.

Performance of SEMCODER SEMCODER, while having only 6.7B parameters, exhibits exceptional performance in code generation and execution reasoning tasks, surpassing larger models like GPT-3.5-turbo and various open-source models. For code generation, SEMCODER variants achieve a pass@1 of 79.3% on HumanEval [1], outperforming GPT-3.5-turbo's 76.8%, and with 27.5% on LiveCodeBench-Lite [18], outperforming GPT-3.5-turbo's 23.9%. For execution reasoning, SEMCODER variants score 63.6%, 65.1%, 61.2% on CRUXEval-I, CRUXEval-O, and LiveCodeBench-CodeExecution, respectively, significantly outperforming baseline models including

<div>

✏️ Approximate Semantics

Implement a function that takes a list of potential energies, sorts them in ascending order, removes duplicates, and returns the indices of the unique sorted energies.

Write a function `unique_sorted_indices(energies: List[float]) -> List[int]` that takes a list of potential energies as input and returns a list of indices corresponding to the unique sorted energies.

🔨 Symbolic Semantics

```python
from typing import List
def unique_sorted_indices(energies: List[float]):
  energy_dict = {}
  for idx, energy in enumerate(energies):
    energy_dict.setdefault(energy, idx)
  sorted_unique_energies = sorted(set(energies))
  unique_sorted_indices = [energy_dict[energy] for energy in
sorted_unique_energies]
  return unique_sorted_indices
```

🔍 Abstract Semantics

Key Properties and Constraints

- The input list can contain duplicate values and is of variable length.
- The output list will have unique energy values sorted in ascending order and will contain their original indices from the input list.
- If an energy value is repeated, only its first occurrence's index is stored in the dictionary.
- The function ensures that the indices in the output list reflect the order of the unique values after sorting.

⚙️ Operational Semantics

Given the input is `[10.5, 8.2, 10.5, 7.1, 8.2]`, let's simulate the execution
1. `energy_dict` is initialized as an empty dictionary.
2. Filling the Dictionary: The `for` loop begins, iterating through the list with `enumerate`:
  - Iter 1: For `idx = 0`, `energy = 10.5`. We update the dictionary to be {10.5: 0}
  ...
  - Iter 5: For `idx = 4`, `energy = 8.2`. Since 8.2 is in the dictionary, it is not updated.
  Final state of `energy_dict`: `{10.5: 0, 8.2: 1, 7.1: 3}`.
3. Sorting Unique Energies: Resulting in `sorted_unique_energies = [7.1, 8.2, 10.5]`.
4. Retrieving Original Indices:
  - For `energy = 7.1`, the index is `3`.
  - For `energy = 8.2`, the index is `1`.
  - For `energy = 10.5`, the index is `0`.
  - Thus, `unique_sorted_indices` becomes `[3, 1, 0]`.
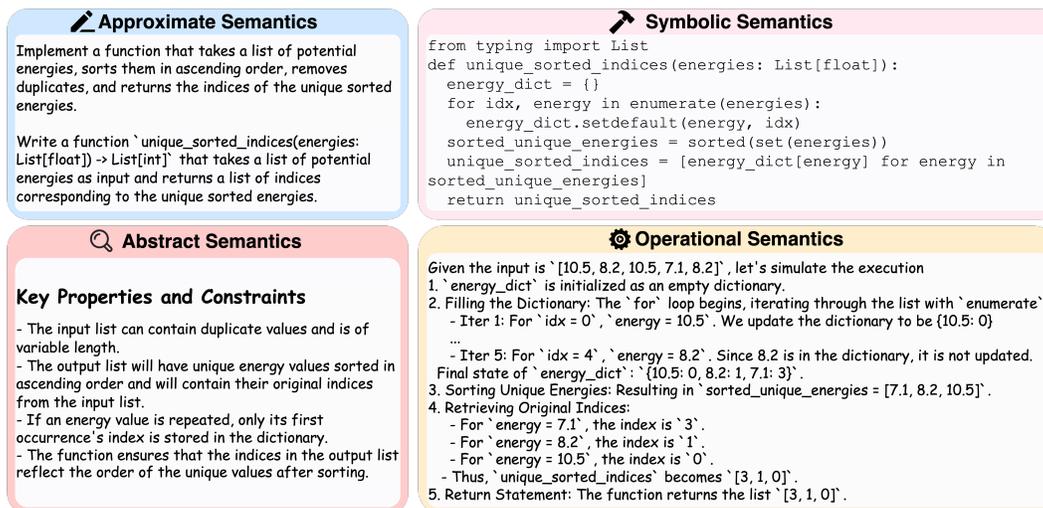5. Return Statement: The function returns the list `[3, 1, 0]`.

</div>

Figure 1: SEMCODER's training strategy with different modalities of program semantics. We specify the overall objective of a task, i.e., the approximate semantics (blue box), such as "retrieves potential energies of atoms and performs sorting" followed by the corresponding code solution (pink box). Then we annotate the abstract code semantics as those key properties and constraints (red box) that hold regardless of inputs. Beyond static semantics, we also pair code with test cases, such as "Given [10.5, 8.2, 10.5, 7.1, 8.2], return [3, 1, 0]". We further annotate the dynamic, operational semantics with forward and backward monologues (yellow box, and more in Section 4.2). SEMCODER learns from all the information to not only generate code but comprehensively reason its semantics.

GPT-3.5-turbo and showcasing its superior understanding of program executions. The innovative monologue reasoning technique, where the model verbalizes code semantics from high-level function-alities to low-level execution details, greatly enhances execution reasoning, outperforming existing trace reasoning formats like scratchpad [2] and NExT [13]. The monologue reasoning approach also allows SEMCODER to flexibly handle abstract semantics and non-deterministic program states, which existing methods struggle with. Additionally, SEMCODER excels in debugging and self-refinement, improving code generation accuracy iteratively by verbally rubber-duck debugging by itself without the need for dynamic tracing. We empirically reveal that SEMCODER's static monologue reasoning is comparably effective as attaching real traces [13] for bug fixing. Besides the effectiveness, monologue reasoning has unique advantages by design: (1) it is purely static reasoning and does not require dynamic tracing, (2) it compacts the execution reasoning by focusing on key properties related to the bug rather than checking all redundant program states and concrete variable values, and (3) it provides a human-readable explanation for better understanding.

Our main contribution is the development of SEMCODER, a semantic-aware Code LM designed to enhance understanding and reasoning about program semantics. We introduce Monologue Reasoning, a novel code reasoning approach that connects static source code with its runtime behavior through detailed verbal descriptions of code properties and runtime behaviors. To expose comprehensive program semantics at different levels, we curate PYX, a collection of executable code samples with functional descriptions and execution traces. SEMCODER demonstrates superior performance in code generation and execution reasoning tasks, surpassing larger open-source models. SEMCODER also excels in debugging and self-refinement by leveraging knowledge from its semantic-aware training. Our work highlights the potential of integrating deep semantic understanding into Code LMs to improve their effectiveness in complex programming tasks.

2 Program Semantics

Program semantics refers to the meaning or behavior of a computer program, describing what it does when it runs, including input processing, computations, and output [19, 20]. Understanding program semantics is crucial for ensuring programs behave correctly and meet their intended purpose.

Program semantics can be represented in various modalities. A high-level description outlines a program's intended functionality, while fine-grained semantics detail the actions and side effects of each line of code, including data manipulation and state changes. This detailed understanding helps developers write better code and aids in code reviewing, debugging, and team communication. Fine-grained semantics can be concrete or abstract. Concrete semantics (e.g., program traces) capture actual execution effects, while abstract semantics focus on key input-output relationships and overall program effects, abstracting away lower-level details [21, 22]. Following the existing literature on program semantics [19, 20], we curate the following semantics.

Approximate Semantics describes the overall objectives of a program, often articulated through docstrings or documentation [23, 24]. These Natural Language descriptions provide an overview of the program's goals and anticipated results, ensuring that the implementation aligns with the intended high-level functionalities (blue box in Figure 1).

Symbolic Semantics represents complex functionality and logic in a way that both humans and machines can interpret consistently. It refers to the layer of meaning derived from the symbols, syntax, and structure of source code (pink box in Figure 1). It describes how code represents high-level functionality and logic by focusing on those constructs within the source code that symbolize particular behaviors, concepts, or operations in the program design.

Operational Semantics describe how the individual steps in a source code execute [25, 19, 20]. It focuses on describing the concrete execution of a program in a step-by-step manner, detailing how each action transforms the program's state. This approach is particularly useful for reasoning about the dynamic behavior of programming languages (yellow box in Figure 1).

Abstract Semantics is a way to describe program behavior at a higher level of abstraction [26, 27, 21, 22]. Unlike concrete semantics, which provides detailed descriptions of the program's execution on specific inputs, abstract semantics focuses on the essential aspects of program behavior while ignoring low-level details. This approach is to reason about program properties and constraints (red box in Figure 1 that always hold.

3   PYX: Semantic-aware Training Dataset

Capturing program semantics requires executing source code with unit tests. Real-world datasets are challenging due to diverse configurations, lack of unit tests, and limited documentation [28]. Thus, we use a synthetic dataset to capture program semantics. Here, we detail the process of gathering high-quality data for learning multi-modal code semantics. Similar to [16, 17], we first synthesize NL to Code pairs. Then, we use the Python interpreter to filter out defective samples, ensuring comprehensive semantic coverage. See Appendix F for more details and analysis, including Figure 4 which depicts the data collection procedure.

3.1   Synthesizing Executable Code

Synthesizing instructional data (NL to code) with existing LLMs is common for obtaining large datasets for instruction tuning CodeLLMs [16, 17]. However, current methods do not guarantee the quality of generated code. For instance, out of 43.1k Python solutions from [16], about 11.6k (26.9%) are inexecutable despite instructions to produce "correct" and "self-contained" code (Table 7 in Appendix F shows the top 10 error types). To build SEMCODER, we train it only with executable data, as good data leads to better generation [29, 30]. We improve the OSS-INSTRUCT data generation process [16], which prompts an LLM to create a programming task and solution inspired by a seed snippet. Instead of randomly sampling lines from existing programs, we parse them into ASTs and sample subtrees to obtain parsable seeds. We execute the generated code, retaining only successfully executed samples, and use the generator model's debugging capability to retry until the code runs correctly. With the low-cost supervision from the Python interpreter, we build a higher-quality instruction tuning dataset for semantic-aware model training. Step I of Figure 4 in Appendix F summarizes this process. Table 2 in Appendix F compares our PYX with OSS-INSTRUCT in details.

3.2   Dataset with Operational Semantics

We select a subset of PYX to construct data to learn the execution reasoning (See Step-II of Figure 4 in Appendix F).
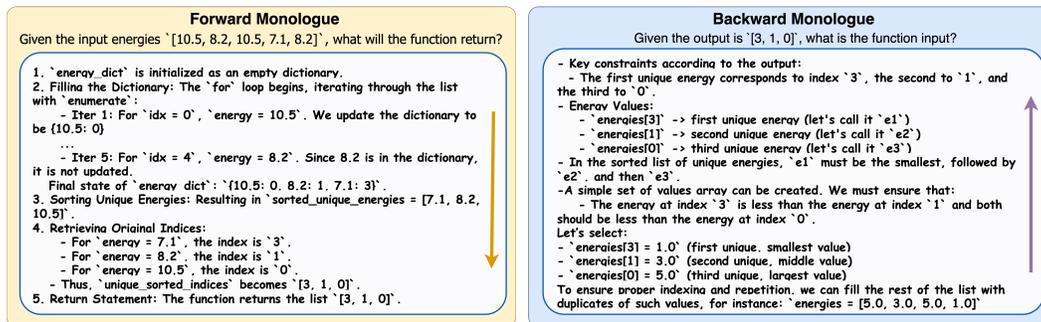
Forward Monologue
Given the input energies `[10.5, 8.2, 10.5, 7.1, 8.2]`, what will the function return?

1. `energy_dict` is initialized as an empty dictionary.
2. Filling the Dictionary: The `for` loop begins, iterating through the list with `enumerate`:
    - Iter 1: For `idx = 0`, `energy = 10.5`. We update the dictionary to be {10.5: 0}
    ...
    - Iter 5: For `idx = 4`, `energy = 8.2`. Since 8.2 is in the dictionary, it is not updated.
    Final state of `energy_dict`: `{10.5: 0, 8.2: 1, 7.1: 3}`.
3. Sorting Unique Energies: Resulting in `sorted_unique_energies = [7.1, 8.2, 10.5]`.
4. Retrieving Original Indices:
    - For `energy = 7.1`, the index is `3`.
    - For `energy = 8.2`, the index is `1`.
    - For `energy = 10.5`, the index is `0`.
    - Thus, `unique_sorted_indices` becomes `[3, 1, 0]`.
5. Return Statement: The function returns the list `[3, 1, 0]`.

Backward Monologue
Given the output is `[3, 1, 0]`, what is the function input?

- Key constraints according to the output:
    - The first unique energy corresponds to index `3`, the second to `1`, and the third to `0`.
- Energy Values:
    - `energies[3]` -> first unique energy (let's call it `e1`)
    - `energies[1]` -> second unique energy (let's call it `e2`)
    - `energies[0]` -> third unique energy (let's call it `e3`)
- In the sorted list of unique energies, `e1` must be the smallest, followed by `e2`, and then `e3`.
- A simple set of values array can be created. We must ensure that:
    - The energy at index `3` is less than the energy at index `1` and both should be less than the energy at index `0`.
Let's select:
- `energies[3] = 1.0` (first unique, smallest value)
- `energies[1] = 3.0` (second unique, middle value)
- `energies[0] = 5.0` (third unique, largest value)
To ensure proper indexing and repetition, we can fill the rest of the list with duplicates of such values, for instance: `energies = [5.0, 3.0, 5.0, 1.0]`

Figure 2: Forward monologue simulates the execution step-by-step, and backward monologue deduces the previous program states by making assumptions and checking with observed constraints.

Data Selection We apply the following filtering criteria to select programs with clean execution flow from our executable dataset: (i) Only programs without external resource interactions (e.g., keyboard input, file system changes) are included, as our trace representation only captures variable state changes. (ii) Programs must have no randomness, ensuring predictable behavior.

Input Generation Our executable dataset typically has one or two example inputs per program. To model operational semantics accurately and avoid bias, we need a diverse input set to expose different execution traces. We expand the input set using type-aware mutation and LLM-based input generation, similar to [31] as detailed in Appendix F.

3.3 PYX-R: Training Code LLMs to Rubber-duck Debug and Self-refine

We construct a debugging dataset, PYX-R, to train Code LLMs for debugging and self-refinement, aiming to improve their iterative programming capabilities. We collect buggy solutions by sampling LLM for problems in PYX and keep those responses that fail at least one of the tests. We perform rejection sampling with LLM to collect rubber-duck debugging rationales for buggy programs and their input sets. PYX-R only includes those rationales that lead to correct patches, verified by differential testing against the ground truth. We provide an example of PyX-R data in Appendix F.

4 SEMCODER: Learning Comprehensive Semantics

4.1 Natural Language to Code

We train SEMCODER to translate high-level functional descriptions into executable code, known as the natural language to code task [16, 17]. Using PYX samples, we provide well-defined problem descriptions that specify (1) the task's overall objective, (2) implementation constraints, and (3) expected outcomes with test cases. These descriptions give a holistic view of the task, forming the basis for the model's understanding.

4.2 Monologue Reasoning to Comprehensively Understand Code Semantics

We train SEMCODER to understand code semantics through monologue reasoning: Given the source code and executable inputs/outputs, the model needs to reason code from high-level abstraction to low-level details, from static perspective to dynamic perspective. Note that the original natural language description of the problem will not be provided to generate monologues.

First, SEMCODER summarizes the high-level functionalities to understand the approximate semantics. Then, SEMCODER will explain the abstract semantics as key properties and constraints that always hold for all executions. Finally, SEMCODER describes the operational semantics by articulating state changes during execution for the provided execution input/output. Inspired by rubber-duck debugging, this approach explains program states transition more smoothly than structured formats like Scratchpad [32], avoiding redundant program states (e.g., numpy array with hundreds of elements) and concrete values (e.g., float numbers) while focusing on key properties that contribute to the code understanding. We detail such effectiveness in Section 6.2. We provide partial monologues for illustration in Figure 2 and full monologues in Appedix G.

4.2.1 Forward Monologue

We provide SEMCODER with the source code and input, and it learns to reason the operational semantics by verbally simulating the execution step by step and predicting the execution output (Figure 2 yellow box).

Execution Coverage   To ensure comprehensive understanding, forward monologue covers those lines with side effects, contributing to a thorough control flow understanding and enforcing a detailed code walkthrough, similar to a developer's debugging process.

Natural Execution Orders   To mimic natural code execution, forward monologue follows the natural order of reasoning. For loops, it explains each iteration with specific values, addressing lines executed multiple times differently. This ensures an accurate, context-aware execution path, similar to how developers mentally simulate execution behavior, helping to detect issues like infinite loops or incorrect condition handling.

Program State Transition   Understanding code side effects is crucial for grasping program state evolution. Forward monologue indicates changes in variable values when a line is executed, enhancing its ability to simulate real execution effects. This focus on side effects helps capture dynamic semantics, providing granular, step-by-step explanations of state changes, thus improving debugging and refinement based on observed behavior.

Final Output   Finally, the model predicts the program's final output after explaining the execution process to validate the correctness of intermediate logic.

4.2.2 Backward Monologue

While forward execution is mostly deterministic, the previous program state cannot always be determined from the current state, such as an unsorted list from its sorted version. Therefore, we design the backward monologue to be flexibly abstract (See Figure 2, blue box).

Abstract Intermediate Constraints   In our backward monologue reasoning, we use abstract intermediate constraints when previous program states can't be uniquely determined from the current state, such as after sorting or aggregation. We train the model to describe these constraints abstractly. This abstraction captures essential characteristics and patterns, allowing the model to reason about multiple possible previous states. This approach enhances the model's flexibility and generalization, improving its ability to handle diverse and complex program reasoning tasks.

Concrete Input   For a given output, the model learns to predict concrete input values that satisfy the input abstract constraints. This step bridges the gap between abstract reasoning and concrete execution. This ensures it understands patterns and can generate practical examples, enhancing its robustness for real-world tasks like debugging and testing. This capability mirrors how human developers perform backward reasoning for debugging [33].

4.2.3 Monologue Annotation Using LLM

To annotate the monologue required for training SEMCODER, we employ a method of rejection sampling [34, 35] through a large language model. We leverage the power of LLM to automatically annotate numerous samples for training SEMCODER, while we have an execution-based golden standard to verify the quality of annotated monologues, ensuring they are informative and valuable, thereby enhancing SEMCODER's ability to reason about program executions both forward and backward.

For forward monologue annotation, we feed code samples from our PyX dataset into an LLM, prompting it to generate a detailed explanation of state changes and transition logic, ending with a final output prediction. We then execute the code; if the actual output matches the LLM's prediction, we accept the monologue, ensuring it accurately reflects the program's execution. If the output does not match, the monologue is rejected. This method ensures the monologue is comprehensive and suitable for training SEMCODER. We follow a similar strategy for backward monologue annotation.

To enhance our monologue annotation process, we provide the LLM with few-shot examples when generating forward and backward monologues. These examples follow our defined rules, explicitly detailing execution lines, variable changes, and reasoning steps for forward monologues, and abstract constraints with specific examples for backward monologues. This guidance ensures the LLM adheres

to our structured reasoning steps. We also use system instructions to ensure the LLM follows the procedures illustrated in the few-shot examples.

4.3   Joint Training with Comprehensive Semantics

SEMCODER is trained with the combined data of natural-language-to-code samples, forward monologues, and backward monologues, using the standard next-token prediction objective [36]. Our training has an emphasis on learning the program semantics, where the training loss is accumulated only by cross-entropy loss on code and monologue tokens together. We also include a task-specific prefix as part of the model input so that the model is better aware of which types of program semantics it should learn to capture and predict for the current sample. See Appendix H for concrete prefixes.

5   Experiments

Code Generation and Execution Reasoning   For code generation evaluation, we consider EvalPlus [31] and the code generation task in LiveCodeBench-Lite (LCB-Lite for short)[18]. For execution reasoning, we employ CRUXEval [37] and the code execution task in LiveCodeBench (LCB-Exec for short) [18]. We prompt the baseline models to perform chain-of-thought reasoning [38] motivated by two-shot examples, and zero-shot prompt SEMCODER to perform monologue reasoning. Inferences all follow the benchmark's original settings.

Rubber-duck Debugging and Self-refine   We evaluate iterative programming capabilities in a setting similar to self-refinement/self-debugging [39, 40] —models generate code, test it, rubber-duck debug the erroneous solution, and refine their code based on the root cause analysis. Using EvalPlus [31], we perform five iterative refinements using greedy decoding. We evaluate models with both zero-shot prompting and fine-tuned using PyX-R settings.

Models   SEMCODER loads the 6.7B base version of DeepSeekCoder as the initial checkpoint and continues to optimize it with the proposed program semantic training. Similar to Magicoder [16], we train two versions of SEMCODER, the base version and the more advanced SEMCODER-S. The base version of SEMCODER is completely trained with PYX. The advanced SEMCODER-S is trained with an extended dataset that includes PYX, Evol-instruct [16], and partial CodeContest [41]. Evol-instruct is a decontaminated version of `evol-codealpaca-v1` [42], which contains numerous instruction-following data. To increase the diversity of coding problems, we sample solutions from CodeContest [41], resulting in 4.3k problems with at least one correct, LLM-generated solution.

Configuration and Empirically Settings   All SEMCODER variants are trained for 2 epochs on a server with eight NVIDIA RTX A6000 GPUs, using a learning rate of 5e-5 with a cosine decay to 5e-6 during the program semantics training. For self-refinement fine-tuning, SEMCODER and baseline Code LLMs are trained for 2 epochs with a learning rate of 1e-5. We use a batch size of 512, a maximum context length of 2,048. Similar to [16], we use `GPT-3.5-turbo` to synthesize coding problems. To minimize the cost, we use `GPT-4o-mini` to generate code solution and monologue reasoning texts, which are typically longer sequences than the problem descriptions.

6   Evaluation

6.1   Overall Performance

In this section, we report the overall performance of SEMCODER for code generation and execution reasoning tasks and compare it with baseline Code LLMs.

Baselines and Evaluation Metric   We consider four families of open-source Code LLMs as baselines: Code Llama [4], StarCoder2 [5], DeepSeekCoder [3], and Magicoder [16]. Despite SEMCODER having only 6.7B parameters, we include 6.7B, 7B, and 13B variants, both base and instruct versions, if publicly available, totaling 13 open-source models. We also compare SEMCODER to GPT-3.5-turbo for code generation and execution reasoning to measure the performance gap with closed-source models. Results are reported with pass@1.

SEMCODER Achieves Dominant Performance in Code Generation and Execution Reasoning
We show the main evaluation results in Table 1. SEMCODER reports dominant performance in execution reasoning, significantly better than other open-source baselines, including those with

Table 1: Overall performance of SEMCODER. For code generation, the numbers outside and inside parenthesis `"()"` indicate the `base` and `plus` versions of EvalPlus, respectively. All results are reported with pass@1. CXEval indicates CRUXEval, and LCB indicates LiveCodeBench.

Model	Size	Code Generation			Execution Reasoning		
		HEval (+)	MBPP (+)	LCB-Lite	CXEval-I	CXEval-O	LCB-Exec
GPT-3.5-Turbo	-	76.8 (70.7)	**82.5 (69.7)**	23.9	50.3	59.0	43.6
CodeLlama-Python	13B	42.7 (38.4)	63.5 (52.6)	10.6	40.5	36.0	23.2
CodeLlama-Inst	13B	49.4 (41.5)	63.5 (53.4)	12.5	45.6	41.2	25.7
StarCoder2	15B	46.3 (37.8)	55.1 (46.1)	16.0	46.9	46.2	33.6
StarCoder2-Inst	15B	67.7 (60.4)	78.0 (65.1)	15.5	47.1	50.9	29.6
CodeLlama-Python	7B	37.8 (35.4)	59.5 (46.8)	7.1	40.4	34.0	23.0
CodeLlama-Inst	7B	36.0 (31.1)	56.1 (46.6)	10.6	36.0	36.8	30.7
StarCoder2	7B	35.4 (29.9)	54.4 (45.6)	11.6	38.2	34.5	26.3
Magicoder-CL	7B	60.4 (55.5)	64.2 (52.6)	11.4	34.0	35.5	28.6
Magicoder-S-CL	7B	70.7 (67.7)	68.4 (56.6)	12.1	42.0	35.8	30.0
DeepSeekCoder	6.7B	47.6 (39.6)	72.0 (58.7)	20.3	39.5	41.2	36.1
DeepSeekCoder-Inst	6.7B	73.8 (70.7)	74.9 (65.6)	21.1	41.9	43.2	34.0
Magicoder-DS	6.7B	66.5 (60.4)	75.4 (61.9)	25.5	45.5	41.9	38.8
Magicoder-S-DS	6.7B	76.8 (71.3)	75.7 (64.4)	23.3	44.6	43.5	38.4
SEMCODER (Ours)	6.7B	73.2 (68.9)	**79.9** (65.3)	22.4	62.5	**65.1**	59.7
SEMCODER-S (Ours)	6.7B	**79.3 (74.4)**	79.6 (**68.5**)	**27.5**	**63.6**	63.9	**61.2**

$2\times$ more parameters. We also collect results for larger models (e.g., CodeLlama-34B) from the benchmark to compare with SEMCODER in Appendix Table 6.

Comparing SEMCODER with its initial checkpoint, DeepSeekCoder-6.7B, our semantic-heavy training strategy brings much stronger execution reasoning capabilities, resulting in a 23.0% absolute improvement for input prediction and 23.9% and 23.6% absolute improvement for CRUXEval-O and LCB-Exec, respectively. Notably, both variants of SEMCODER outperform GPT-3.5-turbo for execution reasoning with a significant margin.

SEMCODER also demonstrates remarkable performance in code generation: SEMCODER achieves 79.9 pass@1 in MBPP, outperforming all open-source baselines, and the advanced version SEM-CODER-S achieves pass@1 of 79.3 and 74.4 for HumanEval base and plus, respectively, significantly beating other models, including GPT-3.5-turbo. These impressive results support Terry Winograd's vision in 1973 [14] that training models to thoroughly understand programs produces more reliable and accurate programming assistants.

Execution Reasoning Requires Comprehensive Understanding of Code Semantics We show results of input/output prediction without reasoning in Appendix Table 5. Interestingly, when comparing the results with reasoning vs. w/o reasoning, we found that the free-form chain-of-thought can hardly help model reason about execution, even if it takes more inference-time computation to generate more tokens. In contrast, monologue reasoning significantly improves the execution reasoning capability by up to 21.7% absolute improvement in output prediction. This empirically reveals that thorough understanding of code execution requires systematic reasoning over comprehensive semantics.

6.2 Effectivenss of Monologue Reasoning

In this section, we perform ablation studies to demonstrate the effectiveness of monologue reasoning.

Baselines We consider two baseline execution reasoning approaches: scratchpad [2] and NeXT's trace format [13]. NeXT adds numeric order to state changes and omits intermediate loop states. We also create a template to concise execution traces, replacing monologue reasoning with concrete program states. Examples are in Appendix I. Additionally, we report few-shot prompting results on the base Code LM using chain-of-thought reasoning [38] without our execution reasoning data.

Experiments We first construct different formats of execution reasoning using the same PYX samples that construct monologues. Then we fine-tune `deepseek-coder-6.7b-base` on these

Table 2: Ablation study for input and output prediction with different types of execution reasoning.

Method	CRUXEval-I	CRUXEval-O	LCB-Exec
Few-shot Prompting	39.5	41.2	36.1
Finetune			
w/ Scratchpad [2]	48.8	50.6	39.9
w/ NeXT [13]	49.4	50.9	32.2
w/ Concise Trace	52.1	55.6	35.9
w/ Monologue Reasoning (Ours)	**61.8**	**63.5**	**58.5**

different execution reasoning data for 3 epochs and compare their results on input and output prediction using CRUXEval.

Monologue Reasoning is More Effective Than Learning Concrete Program States Results in Table 2 show that, while all baselines improve execution reasoning, our monologue reasoning outperforms them in input and output prediction with clear margins. The main reason is that monologues describe state transitions smoothly in natural language while keeping track of only key properties and values, which is easier for code LLMs to learn and understand and consequently enhance execution reasoning. In contrast, baselines provide only concrete states with redundant information and values while not explaining the causal relations of these transitions, so code LLMs struggle to capture the correlation among them.

When we manually check the monologues, which are structured to ensure correct outcomes (Section 4.2.3, we observe that the intermediate logic could be occasionally flawed – the model sometimes makes wrong assumptions about code properties but still reaches the correct result. In contrast, all baselines are guaranteed to have correct intermediate steps, as they are realistic execution traces (See Appendix A for limitation and future work). Empirically, however, the model learns more effectively from the monologues. This highlights the potential benefits of emphasizing key property correctness and model-friendly data format when jointly training code LLMs with distinct semantics.

6.3 Debugging and Self-Refinement

We format the debugging process as verbally and statically explaining why the bug happens [15] to evaluate the code LMs' reasoning capability rather than the tool-using capability that performs dynamic execution with tracers or debuggers. Then the model should fix the bug according to its own reasoning, i.e., self-refine. We provide an example in Appendix F (Example-2) to illustrate how this task is performed.

Experiments We consider four state-of-the-art instruction-tuned code LMs as baselines: Llama-3.1-Instruct-8B [43], DeepSeekCoder-Instruct-6.7B, Magicoder-DS-6.7B, and Magicoder-S-DS-6.7B. We evaluate their static debug and self-refine capabilities on EvalPlus with five iterations. We first evaluate with zero-shot prompting and then also fine-tune with PYX-R to illustrate its value.

Table 3: Performance of iterative debug and self-refine

(a) Zero-shot Prompting

Model	Self-Refine	
	HEval (+)	MBPP (+)
Magicoder-DS	65.2 (60.4)	78.3 (65.9)
Magicoder-S-DS	77.4 (70.1)	79.9 (68.8)
DeepSeekCoder-Inst	77.4 (73.2)	80.4 (69.6)
Llama-3.1-Inst	76.8 (68.9)	77.8 (65.6)
SEMCODER	75.6 (71.3)	83.1 (67.2)
SEMCODER-S	**84.8 (79.3)**	**86.8 (74.3)**

(b) Fine-tuned w/ PYX-R

Model	Self-Refine	
	HEval (+)	MBPP (+)
Magicoder-DS	78.8 (64.3)	83.1 (66.7)
Magicoder-S-DS	83.5 (76.2)	84.4 (71.4)
DeepSeekCoder-Inst	83.5 (75.6)	84.9 (69.6)
Llama-3.1-Inst	76.8 (68.9)	76.7 (61.4)
SEMCODER	76.8 (69.5)	81.7 (65.9)
SEMCODER-S	**85.4 (79.3)**	**87.0 (73.5)**

SEMCODER Reports Promising Performance in Debugging and Self-Refinement In Table 3, SEMCODER-S outperforms all baselines, more notably in the zero-shot setting. This result illustrates that the SEMCODER's monologue reasoning augments general-purpose instruction tuning with code semantics reasoning capabilities. Appendix D demonstrates SEMCODER's continuous code

refinement throughout iterations, showcasing the potential of learned program semantics for complex programming tasks.

PYX-R Improves Iterative Programming Capability   Fine-tuning Code LMs on PYX-R significantly improves iterative programming performance due to the monologue-style debugging rationale and well-aligned patches. PYX-R helps Code LMs understand and analyze bugs from source code and execution traces, aiming to inspire better iterative programming capabilities. We notice that PYX-R provides limited improvement to SEMCODER variants and Llama-3.1-Inst, and we speculate that these models are already trained with high-quality reasoning, and the occasional errors in PyX-R debugging rationale restrict these models from becoming significantly better (See Appendix A).

Monologue Reasoning vs. Execution Traces for Debugging   We perform additional experiments by replacing the monologue reasoning part (See "### Execution Simulation" in Appendix F Example 2) in the debugging rationale with real traces, following the format of NExT [13] and fine-tuning code LMs again. Results are in Appendix C.1. We notice that monologue reasoning is comparably effective as attaching execution traces. Besides the effectiveness, monologue reasoning has unique advantages by design: (1) it is purely static reasoning and does not require dynamic tracing, (2) it compacts the execution reasoning by focusing on key properties related to the bug rather than checking all redundant program states and concrete variable values, and (3) it provides a human-readable explanation for better understanding.

7   Related Work

Code LLMs and Training Data   Many open source Code LLMs, such as CodeGen [44], StarCoder [45, 5], Code Llama [4], and DeepSeek Coder [3], are proposed. Specialized models [32, 1, 41] have also been developed for tasks like code generation, summarization, output prediction, and competitive programming following the success of GPT-3 [46]. These models are trained only on source code and related text, lacking execution context. This limits their understanding of program semantics, leading to security issues and debugging failures. We aim to bridge this gap by training Code LMs on both static source code and dynamic execution traces. An orthogonal line of research curates synthetic instruction-following data to enhance Code LLM performance. Code Alpaca [47] has 20k instruction-response pairs, Evol-Instruct-Code [17] expands this to 80k pairs, and OSS-Instruct [16] includes 75k diverse pairs from the Stack dataset [9]. However, these datasets focus on natural-language-to-code tasks with little coverage of code execution and unverified solutions. To improve correctness, Zheng et al. [48] created a multi-turn conversation dataset with compiler error messages, and Wei et al. [49] incorporated execution by generating test cases and filtering invalid pairs. Yet, no dataset includes simulating and understanding execution traces. We aim to fill this gap (see Section 3).

Learning and Reasoning about Program Executions   Before LLMs, [50, 51] predict simple program outputs using RNNs, GNNs, small transformers, and neural Turing machines. Austin et al. [32] fine-tuned LLMs for execution output prediction with minimal performance gains. Early models predicted final outputs without revealing execution traces. Nye et al. [2] introduced the Scratchpad method for intermediate results, and others [52, 53] fine-tuned UniXcoder [54] for execution traces but didn't evaluate for code generation tasks. We fine-tune a Code LLM to understand program semantics, excelling in code generation, output prediction, and input prediction (see Section 4). Another approach uses execution feedback for debugging Code LLMs. Self-Debugging [39] shows that natural language explanations or unit test results help self-refinement, but execution traces reduce performance. LeTI [55] and CYCLE [40] fine-tune with execution feedback to improve performance, especially for smaller models. NExT [13] generates debugging rationales to mitigate the negative impact of execution traces. Our work shows that a model trained on code generation, output prediction, and input prediction excels in understanding execution feedback and self-refinement (see Table 3).

8   Conclusion

We train SEMCODER to simultaneously learn different modalities of program semantics: Approximate, Symbolic, Operational, and Abstract. We show that such semantics-oriented joint training cultivates a comprehensive understanding of program semantics — SEMCODER or SEMCODER-S achieves SOTA performance, among all less-than-15B open-source models, in not only the code generation and input/output prediction but also tasks that require deep knowledge of both source code and execution execution reasoning like debugging and self-refinement.

Acknowledgement

References

[1] Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Josh Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. Evaluating large language models trained on code, 2021.

[2] Maxwell Nye, Anders Johan Andreassen, Guy Gur-Ari, Henryk Michalewski, Jacob Austin, David Bieber, David Dohan, Aitor Lewkowycz, Maarten Bosma, David Luan, Charles Sutton, and Augustus Odena. Show your work: Scratchpads for intermediate computation with language models, 2021.

[3] Daya Guo, Qihao Zhu, Dejian Yang, Zhenda Xie, Kai Dong, Wentao Zhang, Guanting Chen, Xiao Bi, Y. Wu, Y. K. Li, Fuli Luo, Yingfei Xiong, and Wenfeng Liang. Deepseek-coder: When the large language model meets programming – the rise of code intelligence, 2024.

[4] Baptiste Rozière, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Romain Sauvestre, Tal Remez, Jérémy Rapin, Artyom Kozhevnikov, Ivan Evtimov, Joanna Bitton, Manish Bhatt, Cristian Canton Ferrer, Aaron Grattafiori, Wenhan Xiong, Alexandre Défossez, Jade Copet, Faisal Azhar, Hugo Touvron, Louis Martin, Nicolas Usunier, Thomas Scialom, and Gabriel Synnaeve. Code llama: Open foundation models for code, 2024.

[5] Anton Lozhkov, Raymond Li, Loubna Ben Allal, Federico Cassano, Joel Lamy-Poirier, Noua-mane Tazi, Ao Tang, Dmytro Pykhtar, Jiawei Liu, Yuxiang Wei, Tianyang Liu, Max Tian, Denis Kocetkov, Arthur Zucker, Younes Belkada, Zijian Wang, Qian Liu, Dmitry Abulkhanov, Indraneil Paul, Zhuang Li, Wen-Ding Li, Megan Risdal, Jia Li, Jian Zhu, Terry Yue Zhuo, Evgenii Zheltonozhskii, Nii Osae Osae Dade, Wenhao Yu, Lucas Krauß, Naman Jain, Yixuan Su, Xuanli He, Manan Dey, Edoardo Abati, Yekun Chai, Niklas Muennighoff, Xiangru Tang, Muhtasham Oblokulov, Christopher Akiki, Marc Marone, Chenghao Mou, Mayank Mishra, Alex Gu, Binyuan Hui, Tri Dao, Armel Zebaze, Olivier Dehaene, Nicolas Patry, Canwen Xu, Julian McAuley, Han Hu, Torsten Scholak, Sebastien Paquet, Jennifer Robinson, Carolyn Jane Anderson, Nicolas Chapados, Mostofa Patwary, Nima Tajbakhsh, Yacine Jernite, Carlos Muñoz Ferrandis, Lingming Zhang, Sean Hughes, Thomas Wolf, Arjun Guha, Leandro von Werra, and Harm de Vries. Starcoder 2 and the stack v2: The next generation, 2024.

[6] GitHub. Github copilot: Your ai pair programmer. `https://github.com/features/copilot`, 2021.

[7] Amazon. Amazon codewhisperer: Your ai-powered productivity tool for the ide and command line. `https://aws.amazon.com/codewhisperer/`, 2022.

[8] OpenAI. Chatgpt. `https://chatgpt.com/`, 2022.

[9] Denis Kocetkov, Raymond Li, Loubna Ben Allal, Jia Li, Chenghao Mou, Carlos Muñoz Ferrandis, Yacine Jernite, Margaret Mitchell, Sean Hughes, Thomas Wolf, et al. The stack: 3 tb of permissively licensed source code. arXiv preprint arXiv:2211.15533, 2022.

[10] Alex Gu, Wen-Ding Li, Naman Jain, Theo X. Olausson, Celine Lee, Koushik Sen, and Armando Solar-Lezama. The counterfeit conundrum: Can code language models grasp the nuances of their incorrect generations?, 2024.

[11] Nathaniel Ayewah, William Pugh, David Hovemeyer, J. David Morgenthaler, and John Penix. Using static analysis to find bugs. IEEE Software, 25(5):22–29, 2008.

[12] Brittany Johnson, Yoonki Song, Emerson Murphy-Hill, and Robert Bowdidge. Why don't software developers use static analysis tools to find bugs? In 2013 35th International Conference on Software Engineering (ICSE), pages 672–681, 2013.

[13] Ansong Ni, Miltiadis Allamanis, Arman Cohan, Yinlin Deng, Kensen Shi, Charles Sutton, and Pengcheng Yin. Next: Teaching large language models to reason about code execution, 2024.

[14] Terry Winograd. Breaking the complexity barrier again. In Proceedings of the 1973 Meeting on Programming Languages and Information Retrieval, SIGPLAN '73, page 13–30, New York, NY, USA, 1973. Association for Computing Machinery.

[15] Andrew Hunt and David Thomas. The pragmatic programmer: from journeyman to master. Addison-Wesley Longman Publishing Co., Inc., USA, 2000.

[16] Yuxiang Wei, Zhe Wang, Jiawei Liu, Yifeng Ding, and Lingming Zhang. Magicoder: Source code is all you need. arXiv preprint arXiv:2312.02120, 2023.

[17] Ziyang Luo, Can Xu, Pu Zhao, Qingfeng Sun, Xiubo Geng, Wenxiang Hu, Chongyang Tao, Jing Ma, Qingwei Lin, and Daxin Jiang. Wizardcoder: Empowering code large language models with evol-instruct. arXiv preprint arXiv:2306.08568, 2023.

[18] 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. arXiv preprint arXiv:2403.07974, 2024.

[19] Matthew Hennessy. The semantics of programming languages: an elementary introduction using structural operational semantics. John Wiley & Sons, Inc., 1990.

[20] Glynn Winskel. The formal semantics of programming languages: an introduction. MIT press, 1993.

[21] Carl A Gunter. Semantics of programming languages: structures and techniques. MIT press, 1992.

[22] Joseph E Stoy. Denotational semantics: the Scott-Strachey approach to programming language theory. MIT press, 1981.

[23] Steve McConnell. Code complete. Pearson Education, 2004.

[24] David Thomas and Andrew Hunt. The Pragmatic Programmer: your journey to mastery. Addison-Wesley Professional, 2019.

[25] Gordon D Plotkin. A structural approach to operational semantics. Aarhus university, 1981.

[26] Flemming Nielson, Hanne R Nielson, and Chris Hankin. Principles of program analysis. springer, 2015.

[27] Patrick Cousot and Radhia Cousot. Abstract interpretation: a unified lattice model for static analysis of programs by construction or approximation of fixpoints. In Proceedings of the 4th ACM SIGACT-SIGPLAN symposium on Principles of programming languages, pages 238–252, 1977.

[28] Marcus J Min, Yangruibo Ding, Luca Buratti, Saurabh Pujar, Gail Kaiser, Suman Jana, and Baishakhi Ray. Beyond accuracy: Evaluating self-consistency of code llms. In The Twelfth International Conference on Learning Representations, 2023.

[29] Suriya Gunasekar, Yi Zhang, Jyoti Aneja, Caio César Teodoro Mendes, Allie Del Giorno, Sivakanth Gopi, Mojan Javaheripi, Piero Kauffmann, Gustavo de Rosa, Olli Saarikivi, et al. Textbooks are all you need. arXiv preprint arXiv:2306.11644, 2023.

[30] Yue Yu, Yuchen Zhuang, Jieyu Zhang, Yu Meng, Alexander J Ratner, Ranjay Krishna, Jiaming Shen, and Chao Zhang. Large language model as attributed training data generator: A tale of diversity and bias. Advances in Neural Information Processing Systems, 36, 2024.

[31] Jiawei Liu, Chunqiu Steven Xia, Yuyao Wang, and Lingming Zhang. Is your code generated by chatgpt really correct? rigorous evaluation of large language models for code generation. Advances in Neural Information Processing Systems, 36, 2024.

[32] Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, et al. Program synthesis with large language models. ArXiv preprint, abs/2108.07732, 2021.

[33] Marcel Böhme, Ezekiel O. Soremekun, Sudipta Chattopadhyay, Emamurho Ugherughe, and Andreas Zeller. Where is the bug and how is it fixed? an experiment with practitioners. In Proceedings of the 2017 11th Joint Meeting on Foundations of Software Engineering, ESEC/FSE 2017, page 117–128, New York, NY, USA, 2017. Association for Computing Machinery.

[34] George Casella, Christian P. Robert, and Martin T. Wells. Generalized accept-reject sampling schemes. Lecture Notes-Monograph Series, 45:342–347, 2004.

[35] Radford M. Neal. Slice sampling, 2000.

[36] Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. OpenAI preprint, 2019.

[37] Alex Gu, Baptiste Rozière, Hugh Leather, Armando Solar-Lezama, Gabriel Synnaeve, and Sida I. Wang. Cruxeval: A benchmark for code reasoning, understanding and execution. arXiv preprint arXiv:2401.03065, 2024.

[38] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models, 2023.

[39] Xinyun Chen, Maxwell Lin, Nathanael Schärli, and Denny Zhou. Teaching large language models to self-debug, 2023.

[40] Yangruibo Ding, Marcus J. Min, Gail Kaiser, and Baishakhi Ray. Cycle: Learning to self-refine the code generation, 2024.

[41] 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. ArXiv preprint, abs/2203.07814, 2022.

[42] theblackcat102. The evolved code alpaca dataset. https://huggingface.co/datasets/theblackcat102/evol-codealpaca-v1, 2023.

[43] Meta Llama Team. The llama 3 herd of models, 2024.

[44] Erik Nijkamp, Bo Pang, Hiroaki Hayashi, Lifu Tu, Huan Wang, Yingbo Zhou, Silvio Savarese, and Caiming Xiong. Codegen: An open large language model for code with multi-turn program synthesis. In International Conference on Learning Representations, pages 1–25, 2023.

[45] Raymond Li, Loubna Ben Allal, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc Marone, Christopher Akiki, Jia Li, Jenny Chim, et al. Starcoder: may the source be with you! arXiv preprint arXiv:2305.06161, 2023.

[46] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In Hugo Larochelle, Marc'Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin, editors, Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual, pages 1–25, 2020.

[47] Sahil Chaudhary. Code alpaca: An instruction-following llama model for code generation. https://github.com/sahil280114/codealpaca, 2023.

[48] Tianyu Zheng, Ge Zhang, Tianhao Shen, Xueling Liu, Bill Yuchen Lin, Jie Fu, Wenhu Chen, and Xiang Yue. Opencodeinterpreter: Integrating code generation with execution and refinement, 2024.

[49] Yuxiang Wei, Federico Cassano, Jiawei Liu, Yifeng Ding, Naman Jain, Harm de Vries, Leandro von Werra, Arjun Guha, and Lingming Zhang. Starcoder2-instruct: Fully transparent and permissive self-alignment for code generation, 2024.

[50] Wojciech Zaremba and Ilya Sutskever. Learning to execute, 2015.

[51] Alex Graves, Greg Wayne, and Ivo Danihelka. Neural turing machines, 2014.

[52] Chenxiao Liu, Shuai Lu, Weizhu Chen, Daxin Jiang, Alexey Svyatkovskiy, Shengyu Fu, Neel Sundaresan, and Nan Duan. Code execution with pre-trained language models, 2023.

[53] Yangruibo Ding, Benjamin Steenhoek, Kexin Pei, Gail Kaiser, Wei Le, and Baishakhi Ray. Traced: Execution-aware pre-training for source code. In Proceedings of the 46th IEEE/ACM International Conference on Software Engineering, pages 1–12, 2024.

[54] Daya Guo, Shuai Lu, Nan Duan, Yanlin Wang, Ming Zhou, and Jian Yin. Unixcoder: Unified cross-modal pre-training for code representation. arXiv preprint arXiv:2203.03850, 2022.

[55] Xingyao Wang, Hao Peng, Reyhaneh Jabbarvand, and Heng Ji. Leti: Learning to generate from textual interactions, 2024.

[56] Hunter Lightman, Vineet Kosaraju, Yuri Burda, Harrison Edwards, Bowen Baker, Teddy Lee, Jan Leike, John Schulman, Ilya Sutskever, and Karl Cobbe. Let's verify step by step. In The Twelfth International Conference on Learning Representations, 2024.

[57] bigcode-project/bigcode-dataset. https://github.com/bigcode-project/bigcode-dataset. (Accessed on 05/17/2024).

A Limitations and Future Work

Process Supervision for Intermediate Reasoning Steps   We manually review the monologues in PYX and the rubber-duck debugging rationales in PYX-R, which are structured to ensure correct outcomes (see Section 4.2.3). While the final answers are accurate, we observed that the intermediate reasoning steps are occasionally flawed. Sometimes, the model makes incorrect assumptions about code properties but still reaches the right result, i.e., correct execution input/output and correct patch. Conceptually, such subtle mistakes in the intermediate reasoning steps might have negative impacts on further improving models' code reasoning capability.

We encourage future work to propose automatic and efficient process supervision approaches [56] specifically for code reasoning, which will be useful to further improve the quality of monologues in PYX.

Curation of Monologue Annotation   The monologue annotation data (Section 4.2.3) is crucial for SEMCODER to excel at the output prediction and input prediction tasks. However, we rely on a more powerful LLM, GPT-3.5-Turbo or GPT-4o-mini to generate these annotations and employ rejection sampling from its responses, since our base model is relatively small with 6.7B parameters.

We encourage future work to try our semantic-oriented joint training on a larger base model, so that it will be possible to generate the monologue annotations using the base model itself like Ni et al. [13] did to bootstrap high-quality reasoning for self-refinement.

Incorporating Execution Reasoning into Code Generation   We demonstrate that training on input and output prediction tasks are indirectly beneficial for both natural-language-to-code generation and downstream tasks like self-refinement. However, there is a more direct way to further improve the performance in code generation and self-refinement — we can ask the model to first self-verify its own solution by generating forward monologue (Section 4.2.1) for the test cases given in the natural language specification before finalizing the solution.

We encourage future work to explore the possibility of using a model's own execution reasoning ability to directly assist its code generation and self-refinement process.

B Broader Impacts

Social Impact   In this work, we train a semantic-aware Code LMs. We make all the data, code, and model checkpoints available publicly. The artifact could be used to deploy automated programming assistants that improve the developers' productivity. It is possible but unlikely that the Code LMs will generate buggy or wrong code, but we suggest to use our models as "copilot" to assist with human developers rather than completely relying on the model for full automation.

Safeguards   Our data is synthesized using a commercial LLM, i.e., GPT-3.5-turbo, which has been aligned by the releasing company, OpenAI, to avoid leaking personal or malicious information. We regard our data has minimal risk of being misused due to its synthetic instinct.

C More Evaluation Results

C.1 Debug and Self-refine w/ Real Execution Traces

Table 4: Debug and self-refine with real traces in the format of NExT [13].

Model	Self-Refine	
	HEval (+)	MBPP (+)
Magicoder-DS	72.0 (66.5)	83.3 (67.5)
Magicoder-*S*-DS	81.7 (74.4)	83.9 (72.0)
DeepSeekCoder-Inst	84.8 (79.9)	85.4 (70.4)
Llama-3.1-Inst	76.2 (69.5)	82.8 (66.7)
SEMCODER	78.0 (70.7)	83.6 (66.4)
SEMCODER-*S*	**86.0 (80.5)**	**87.0 (73.3)**

C.2 Input/Output Prediction Without Reasoning

In Table 5, we present the results of direct prediction for execution input and output without reasoning.

Table 5: Performance of direct prediction for execution input/output w/o reasoning.

Model	Size	Execution Reasoning		
		CRUXEval-I	CRUXEval-O	LCB-Exec
GPT-3.5-Turbo	-	49.0	49.4	39.2
CodeLlama-Python	13B	38.5	39.7	36.1
CodeLlama-Inst	13B	47.5	40.8	33.8
StarCoder2	15B	47.2	46.9	34.7
StarCoder2-Inst	15B	47.4	47.1	8.1
CodeLlama-Python	7B	37.3	34.6	31.1
CodeLlama-Inst	7B	34.8	35.6	30.1
StarCoder2	7B	34.2	35.6	34.0
Magicoder-CL	7B	32.0	35.6	32.4
Magicoder-S-CL	7B	36.2	34.8	30.5
DeepSeekCoder	6.7B	42.2	43.6	44.5
DeepSeekCoder-Inst	6.7B	34.9	40.8	41.1
Magicoder-DS	6.7B	41.2	43.4	38.4
Magicoder-S-DS	6.7B	42.1	44.4	39.2
SEMCODER (Ours)	6.7B	46.9	47.9	38.0
SEMCODER-S (Ours)	6.7B	47.6	46.6	40.7

C.3 Comparison with Larger Open-Sourced Models and Closed-Source Models

Model	Size	Code Generation		Execution Reasoning	
		HEval (+)	MBPP (+)	CRUXEval-I	CRUXEval-O
GPT-3.5-Turbo-1106	-	76.8 (70.7)	82.5 (69.7)	49.0 / 50.3	49.4 / 59.0
Claude-3-Opus	-	82.9 (77.4)	**89.4 (73.3)**	64.2 / 73.4	65.8 / **82.0**
GPT-4-0613	-	88.4 (79.3)	-	**69.8** / 75.5	**68.7** / 77.1
GPT-4-Turbo-2024-04-09	-	**90.2 (86.6)**	-	68.5 / **75.7**	67.7 / **82.0**
CodeLlama	34B	51.8 (43.9)	69.3 (56.3)	47.2 / 50.1	42.4 / 43.6
DeepSeekCoder	33B	51.2 (44.5)	-	46.5 / -	48.6 / -
DeepSeekCoder-Inst	33B	81.1 (75.0)	80.4 (70.1)	46.5 / -	49.9 / -
SEMCODER (Ours)	6.7B	68.3 (62.2)	**79.9** (65.9)	**51.2** / 52.6	**48.1** / 56.6
SEMCODER-S (Ours)	6.7B	**81.1 (76.2)**	78.8 (**66.9**)	48.1 / **54.5**	44.9 / 54.1

Table 6: Overall performance of SEMCODER vs. other Code LLMs. For code generation, the numbers outside and inside parenthesis "()" indicate the base and plus versions of EvalPlus, respectively. For execution reasoning, the left side and the right side of the slash "/" indicate the direct prediction and prediction with reasoning, respectively. All results are reported with pass@1.

D SEMCODER Continuously Refines Code Qualities

We studied SEMCODER's code generation accuracy at each step of refinement with varied temperatures. The results are plotted in Figure 3. We observed that SEMCODER is capable of continuously refining its own errors, and the increase does not stop when the temperature is high, which indicates the SEMCODER has strong debugging and self-refine capabilities and a high temperate better leverages such capabilities for iterative programming.
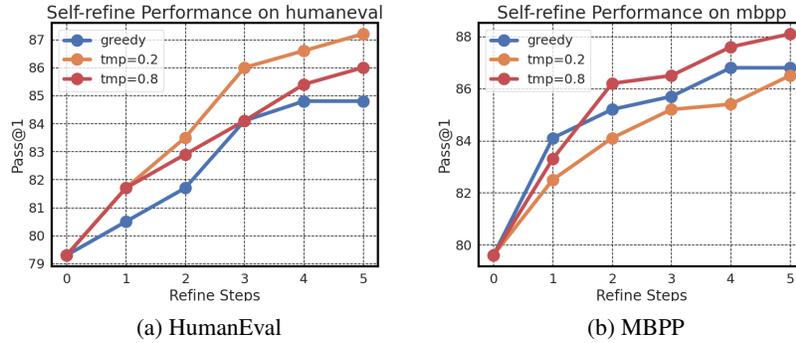
Figure 3: SEMCODER-S's zero-shot performance of self-refinement at each time step with different sampling strategies.

E   Executability Analysis of OSS-INSTRUCT

Table 7: Top-10 error types of inexecutable Python code in OSS-Instruct[16]

Error Type	#Cases out of 43.1k Python samples
ModuleNotFoundError	3417
NameError	1954
FileNotFoundError	1052
ImportError	979
EOFError	743
SyntaxError	672
IndentationError	506
AttributeError	213
TypeError	196
ValueError	132

We execute all Python samples in OSS-INSTRUCT [16] to analyze their executability. To get a more accurate result, we try to mitigate the `ModuleNotFoundError` by installing the top 75 missing dependencies according to a pre-run result. Table 7 shows the breakdown of the top 10 error types.

F   Details on PYX

The whole data collection pipeline is shown in Figure 4. Here we also document more details about PYX.

Prompt for Data Synthesis   We follow the prompt in OSS-INSTRUCT for data synthesis, but with two modifications: 1) For problem design, instruct the model to avoid interaction with external resources or requirement of uncommon third-party libraries to increase the probability of getting executable code. 2) For giving solutions, instruct the model to show its thought process before writing code to produce more aligned natural language along with the code in the dataset. Table 10 details our prompts with an example in PYX.

Input Set Expansion   To enlarge the input set, we first initialize the input corpus with all known valid inputs. Then, for type-aware mutation, we alter known inputs based on type-specific heuristics. For LLM-based generation, we prompt the model with the function and several known inputs to generate more. We verify new inputs by executing them, retaining only those that execute successfully without exceptions. We alternate between type-aware mutation and LLM-based generation until reaching a predefined threshold, combining mutation's efficiency with LLM generation's robustness. The generated inputs and their outputs serve as unit tests for the NL-described task in future steps.
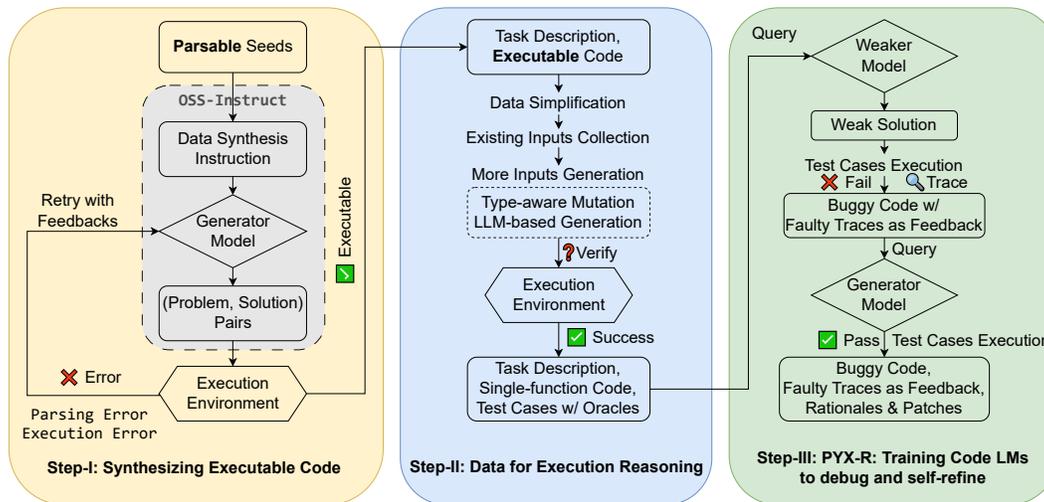
Figure 4: PYX: Execution-aware Training Data Collection Strategy

Table 8: The comparison between OSS-INSTRUCT and our PYX.

| Dataset | Problems | Seed | Solution | | Performance | |
		Parse	Parse	Execute	HumanEval (+)	MBPP (+)
OSS-INSTRUCT	75k	-	-	Partially	67.1 (61.0)	77.5 (64.3)
OSS-INSTRUCT-Python	43k	48%	97%	73%	66.5 (59.8)	**78.6 (65.9)**
PYX (Ours)	32k	100%	100%	100%	**70.1 (64.0)**	**78.6** (65.1)

Coverage of Inputs Our input generation method only considers diversity in terms of variable values but does not try to fully exercise different execution paths in an executable code, like what the coverage-guided testing usually does. However, our dataset only consists of relatively short single-function programs that do not have complicated branches. We find that our generated inputs can achieve average branch coverage and average line coverage of 93%, 96% respectively, which shows that our approach is light-weight yet effective for the current setting.

Executability v.s. Parsability Along with the generation of 34k executable data, we also get 13k samples that can only be parsed as valid ASTs but cannot be successfully executed. We include these parsable samples to form a 47k dataset, PYX-SOFT, and compare it against the fully executable one PYX. Results in Table 8 show that PYX-SOFT and PYX have comparable results, and both of them outperform OSS-INSTRUCT and its Python subset. Though PYX-SOFT sometimes slightly outperforms PYX, full executability is required for comprehensive semantic coverage, so we use PYX for the main evaluation.

Data De-duplication We follow the data decontamination process of [16] and [57] to clean our dataset. To examine the similarity between our instruction tuning dataset and the testing benchmarks, we evaluate the "edit similarity" between them, specifically by scaling the metric `fuzz.partial_token_sort_ratio` provided by `thefuzz` library. For each sample in our dataset, its similarity to a benchmark is computed as the maximum cosine similarity to any sample in the benchmark. We apply the same analysis to OSS-INSTRUCT for comparison. Figure 5 shows that the similarity between our dataset and the two benchmarks is on par with OSS-INSTRUCT, where the majority has less than 0.4 similarity, which indicates that the performance improvement brought by our dataset is not from data leakage or benchmark data imitation.

Categories To study the effect of executability filtering, we categorize all samples in our dataset following [16] shown by Figure 6. Compared to OSS-INSTRUCT, the categorical distribution shifts by an increase in algorithmic and data structure problems, data science and machine learning problems, and mathematical and computational problems, and a decrease in the remaining categories, which is expected since interactions with external resources commonly required in scenarios like database, web and UI design are not allowed in our execution environment.
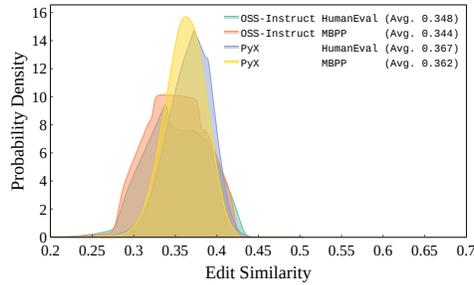
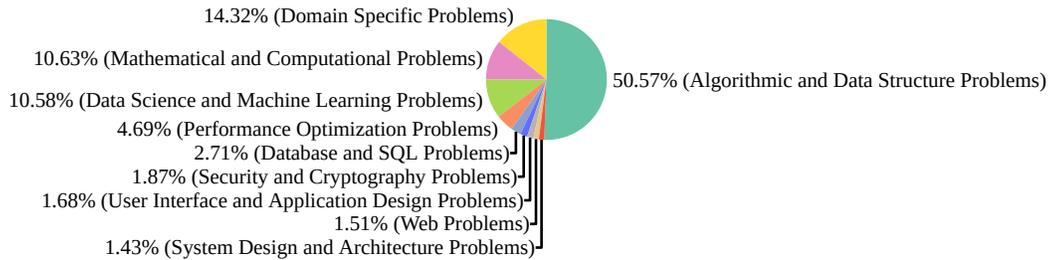Figure 5: Edit similarities between PYX and two popular benchmarks

Figure 6: The category distribution of PYX

Data Statistics We perform decontamination on the PYX, and monologue samples (we remove the samples that share the same input and output pair with CRUXEval). PYX includes 32,489 natural language to code pairs. We generated 29,945 forward monologues and 31,022 backward monologues using rejection sampling. SEMCODER is trained with 93.4k samples, and SEMCODER-S with 214.1k samples. PYX-R contains 18,473 debugging samples, each with the original description, buggy code, debugging rationale, and final patch.

Example 1: An example of PYX sample generation

User Prompt:

```
Please gain inspiration from the following random code snippet to create a high-quality
programming problem. Present your output in two distinct sections: [Problem Description]
and [Solution].

Code snippet for inspiration:
```

testinfra_hosts = testinfra.utils.ansible_runner.AnsibleRunner(
    os.environ["MOLECULE_INVENTORY_FILE"]
).get_hosts("instance")

def test_non_root_user(host):
    with host.sudo(user="vagrant"):
        cmd = host.run_test(command="docker container run hello-world")
    assert "Hello from Docker!" in cmd.stdout

def test_docker_group_members(host):
    content = host.file(path="/etc/group").content_string
    match = re.search(
        pattern=r"^docker:x:\d+:vagrant$",
        string=content,
        flags=re.MULTILINE,
)
    assert match
```

https://doi.org/10.52202/079017-1927

```
Guidelines for each section:

1. [Problem Description]: This should be concise and **completely self-contained**,
providing all the contextual information one needs to understand and solve the problem.
Assume common programming knowledge, but ensure that any specific context, variables, or
code snippets pertinent to this problem are explicitly included. Avoid interaction with
external resources (e.g. keyboard, file system, databases, network) or requirement of
uncommon third-party libraries. The problem should be non-trivial and require some
thought to solve.

2. [Solution]: First, show your thought process and outline your planned steps clearly.
Then offer a comprehensive, **correct** and runnable solution that accurately addresses
the [Problem Description] you provided.
```

Model Response:

```
[Problem Description]
Write a solution to the following coding problem:
You are tasked with creating a Python function that processes a given string to extract
specific information based on predefined patterns. The function should take a string as
input and return a dictionary containing counts of various elements found in the input
string.

The function should perform the following tasks:
1. Count the occurrences of each unique word in the input string.
2. Identify and count the occurrences of any email addresses present in the input string.
3. Determine the total count of numeric digits (0-9) in the input string.

For example, given the input string "Hello world, my email is example@email.com and my
phone number is 12345", the function should return a dictionary like this:
{
    'word_counts': {'Hello': 1, 'world': 1, 'my': 2, 'email': 1, 'is': 2, 'example@email.
com': 1, 'and': 1, 'phone': 1, 'number': 1},
    'email_count': 1,
    'digit_count': 5
}

Ensure that the function is case-insensitive when counting words and email addresses.
Words are defined as sequences of characters separated by spaces, and email addresses
follow the standard format of "example@email.com".

[Solution]
To solve this problem, we will create a Python function that processes the input string
according to the specified requirements. Here is an outline of the planned steps:
1. Initialize variables to store word counts, email count, and digit count.
2. Tokenize the input string into words.
3. Iterate through the words to count occurrences and identify email addresses.
4. Count the total number of digits in the input string.
5. Return a dictionary containing the word counts, email count, and digit count.

Here is the Python function implementing the solution:
```
```python
import re

def process_string(input_string):
    word_counts = {}
    email_count = 0
    digit_count = 0

    words = input_string.lower().split()

    for word in words:
        if re.match(r"[a-zA-Z]+", word):
            word_counts[word] = word_counts.get(word, 0) + 1
        if re.match(r"[a-zA-Z0-9._%+-]+@[a-zA-Z0-9.-]+\.[a-zA-Z]{2,}", word):
            email_count += 1
        digit_count += sum(1 for char in word if char.isdigit())

    return {
        'word_counts': word_counts,
        'email_count': email_count,
        'digit_count': digit_count
    }

# Test the function with an example input
input_string = "Hello world, my email is example@email.com and my phone number is 12345"
result = process_string(input_string)
print(result)
```

```
```

This function processes the input string as described in the problem and returns a
dictionary with the counts of words, email addresses, and digits. The regular expressions
 used help identify words, email addresses, and digits accurately.

Example 2: An example of PYX-R rubber-duck debugging and bug fixing

Prompt:

```
### Problem
Write a solution to the following coding problem:
You are tasked with implementing a Python class that processes and represents data from
HTML soup objects. The class has three methods: `__init__`, `__str__`, and `__repr__`.
The `__init__` method takes a `soup` object, removes empty elements, and parses the input
. The `__str__` and `__repr__` methods return the object's data in JSON format.

Your task is to complete the implementation of the class by defining the `
_remove_empty_elements` and `_parse_input` methods. The `_remove_empty_elements` method
should remove any empty elements from the `soup` object, and the `_parse_input` method
should process the `soup` object to extract relevant data.

Implement the missing methods to ensure that the class functions correctly and outputs
data in JSON format when the `__str__` or `__repr__` methods are called.

### Buggy Solution

```python
from bs4 import BeautifulSoup
import json

class HtmlDataProcessor:
    def __init__(self, soup):
        self.soup = soup
        self.data = {}
        self._remove_empty_elements()
        self._parse_input()

    def _remove_empty_elements(self):
        # Remove empty tags from the soup
        for element in self.soup.find_all(True):  # True finds all tags
            if not element.get_text(strip=True):  # If the element is empty
                element.decompose()  # Remove it from the soup

    def _parse_input(self):
        # Extract relevant data from the soup
        self.data = {}
        for element in self.soup.find_all(True):  # Iterate over all tags
            if element.name in self.data:
                self.data[element.name].append(element.get_text(strip=True))
            else:
                self.data[element.name] = [element.get_text(strip=True)]

    def __str__(self):
        return json.dumps(self.data, ensure_ascii=False)

    def __repr__(self):
        return json.dumps(self.data, ensure_ascii=False)
```
Failed Test
```python
# Test cases to verify the implementation

# Test with a simple HTML soup
html_content = "<div><p>Hello</p><p></p><span>World</span></div>"
soup = BeautifulSoup(html_content, 'html.parser')
processor = HtmlDataProcessor(soup)
assert str(processor) == '{"div": [], "p": ["Hello"], "span": ["World"]}'
```
```

**Target:**

[MONOLOGUE]
### Execution Simulation
Let's walk through the execution of the provided test case with the buggy `HtmlDataProcessor` implementation.

1. **Input HTML**: The test input is:
   ```html
   <div><p>Hello</p><p></p><span>World</span></div>
   ```
   - This gets parsed into a BeautifulSoup object `soup`.

2. **Initialize `HtmlDataProcessor`**: When `HtmlDataProcessor(soup)` is called:
   - `self.soup` is set to the parsed HTML.
   - `self.data` is initialized as an empty dictionary.
   - `_remove_empty_elements()` and `_parse_input()` are invoked sequentially.

3. **Execution of `_remove_empty_elements`**:
   - The method iterates over all elements in `soup`:
     - `<div>`: Not empty (it has children), so it remains.
     - `<p>Hello</p>`: Not empty, so it remains.
     - `<p></p>`: Empty, so it gets decomposed (removed).
     - `<span>World</span>`: Not empty, so it remains.
   - After this process, the `soup` now looks like:
     ```html
     <div><p>Hello</p><span>World</span></div>
     ```

4. **Execution of `_parse_input`**:
   - The method iterates over all tags again:
     - For `<div>`: It adds child elements' texts, resulting in:
       ```python
       self.data['div'] = ['HelloWorld']
       ```
     - For `<p>`: It adds its text "Hello":
       ```python
       self.data['p'] = ['Hello']
       ```
     - For `<span>`: It adds its text "World":
       ```python
       self.data['span'] = ['World']
       ```
   - At the end of this method, `self.data` is:
     ```python
     {'div': ['HelloWorld'], 'p': ['Hello'], 'span': ['World']}
     ```

5. **String Representation**:
   - The `__str__` method is called, producing:
     ```json
     '{"div": ["HelloWorld"], "p": ["Hello"], "span": ["World"]}'
     ```

6. **Test Assertion**: The assertion `assert str(processor) == '{"div": [], "p": ["Hello"], "span": ["World"]}'` fails because the expected output for `div` is an empty list, while the generated output has `"HelloWorld"`.

Root Cause Analysis
The primary issue lies within the `_parse_input` method. Specifically, it collects text from child elements under tags like `<div>`, which makes `self.data['div']` incorrectly aggregated with text from its children, rather than displaying children separately.

Bug Fixing
To fix this, we should prevent the parent tag from aggregating text that includes child elements. Instead, we should only include text for elements that do not have child elements in `_parse_input`. Here's the corrected implementation:
[/MONOLOGUE]
[Refined]
```python

60296

```python
from bs4 import BeautifulSoup
import json

class HtmlDataProcessor:
    def __init__(self, soup):
        self.soup = soup
        self.data = {}
        self._remove_empty_elements()
        self._parse_input()

    def _remove_empty_elements(self):
        # Remove empty tags from the soup
        for element in self.soup.find_all(True):  # True finds all tags
            if not element.get_text(strip=True):  # If the element is empty
                element.decompose()  # Remove it from the soup

    def _parse_input(self):
        # Extract relevant data from the soup
        self.data = {}
        for element in self.soup.find_all(True):  # Iterate over all tags
            if not element.find_all(True):  # Only process elements without child
elements
                element_text = element.get_text(strip=True)
                if element.name in self.data:
                    self.data[element.name].append(element_text)
                else:
                    self.data[element.name] = [element_text]
            else:
                # If this element has children, you can initialize it with an empty list
                if element.name not in self.data:
                    self.data[element.name] = []

    def __str__(self):
        return json.dumps(self.data, ensure_ascii=False)

    def __repr__(self):
        return json.dumps(self.data, ensure_ascii=False)
```
```
[/Refined]
```

G   Detailed Example of Monologues

We provide examples for the detailed forward and backward monologues.

Example Monologue Reasoning

Code and Input:
```python
from typing import List
def unique_sorted_indices(energies: List[float]) -> List[int]:
    energy_dict = {}
    for idx, energy in enumerate(energies):
        energy_dict.setdefault(energy, idx)
    sorted_unique_energies = sorted(set(energies))
    unique_sorted_indices = [energy_dict[energy] for energy in sorted_unique_energies]
    return unique_sorted_indices
assert unique_sorted_indices([10.5, 8.2, 10.5, 7.1, 8.2]) == ??
```

Forward Monologue:

Understanding the Function
The function `unique_sorted_indices` takes a list of floating-point numbers named `energies` as input. Its purpose is to find the indices of the unique elements in the input list when sorted in ascending order.
- A dictionary `energy_dict` is created to map each unique energy value to its first occurrence index.
- The `enumerate` function is used to iterate through the list and populate the dictionary with energy as keys and their respective indices as values.
- Then, the function creates a sorted list of unique energy values from the input list using `sorted(set(energies))`.
- Finally, it creates a list of indices that correspond to these sorted unique energies using a list comprehension that retrieves the original indices from the dictionary.

Key Properties and Constraints
- The input list can contain duplicate values and is of variable length.
- The output list will have unique energy values sorted in ascending order and will contain their original indices from the input list.
- If an energy value is repeated, only its first occurrence's index is stored in the dictionary.
- The function ensures that the indices in the output list reflect the order of the unique values after sorting.

Execution Simulation:
Let's simulate the execution of `unique_sorted_indices([10.5, 8.2, 10.5, 7.1, 8.2])` step by step.

1. **Initialization**:
   - `energy_dict` is initialized as an empty dictionary.

2. **Filling the Dictionary**:
   - The `for` loop begins, iterating through the list with `enumerate`:
     - **Iteration 1**: For `idx = 0`, `energy = 10.5`. The dictionary is updated to `{10.5: 0}`.
     - **Iteration 2**: For `idx = 1`, `energy = 8.2`. The dictionary is updated to `{10.5: 0, 8.2: 1}`.
     - **Iteration 3**: For `idx = 2`, `energy = 10.5`. Since 10.5 already exists in the dictionary, it is not updated.
     - **Iteration 4**: For `idx = 3`, `energy = 7.1`. The dictionary is updated to `{10.5: 0, 8.2: 1, 7.1: 3}`.
     - **Iteration 5**: For `idx = 4`, `energy = 8.2`. Since 8.2 already exists in the dictionary, it is not updated.

   Final state of `energy_dict` after the loop: `{10.5: 0, 8.2: 1, 7.1: 3}`.

3. **Sorting Unique Energies**:
   - The unique energies are derived and sorted, resulting in `sorted_unique_energies = [7.1, 8.2, 10.5]`.

4. **Retrieving Original Indices**:
   - A list comprehension retrieves the original indices corresponding to these sorted unique energies:
     - For `energy = 7.1`, the index is `3`.
     - For `energy = 8.2`, the index is `1`.
     - For `energy = 10.5`, the index is `0`.
   - Thus, `unique_sorted_indices` becomes `[3, 1, 0]`.

5. **Return Statement**:
   - The function returns the list `[3, 1, 0]`.

assert unique_sorted_indices([10.5, 8.2, 10.5, 7.1, 8.2]) == [3, 1, 0]

Code and Output:

```python
from typing import List
def unique_sorted_indices(energies: List[float]) -> List[int]:
    energy_dict = {}
    for idx, energy in enumerate(energies):
        energy_dict.setdefault(energy, idx)
    sorted_unique_energies = sorted(set(energies))
    unique_sorted_indices = [energy_dict[energy] for energy in sorted_unique_energies]
    return unique_sorted_indices
assert unique_sorted_indices(??) == [3, 1, 0]
```

Backward Monologue:

Understanding the Function
The function `unique_sorted_indices` processes a list of floating-point numbers (`energies`) to produce the indices of the unique values sorted in ascending order. Here's how it works:
1. **Initialization**: An empty dictionary `energy_dict` is created.
2. **Dictionary Population**: The function iterates through `energies` using `enumerate`, which provides both the index (`idx`) and the value (`energy`):
    - It uses `setdefault` to record the index for each unique energy value found in the list. If the energy value already exists in the dictionary, it does not update the index (thus only the first index is stored).
3. **Sorting Unique Energies**: A set of unique energy values is created from the list, which is then sorted to create `sorted_unique_energies`.
4. **Index Retrieval**: A new list of indices is constructed by retrieving the original indices from `energy_dict` corresponding to the sorted unique energies.
5. **Return Value**: The function returns a list of indices corresponding to unique energy values in sorted order.

Key Properties and Constraints
- The input list may contain duplicate energy values, but only the first occurrence's index will be recorded in `energy_dict`.
- The output will be ordered according to the sorted unique energy values.
- The length of the output list will equal the number of unique energy values in the input list.

Reverse Deduction
Given the output `[3, 1, 0]`, we need to determine what `energies` might have been to produce this result:
- **Behind the Result**:
    - `energy_dict` must map some unique energies to these indices.
    - The first unique energy corresponds to index `3`, the second unique to `1`, and the third unique to `0`.
- **Energy Values**:
    - Suppose the values in the `energies` list that correspond to these indices are:
        - `energies[3]` -> first unique energy (let's call it `e1`)
        - `energies[1]` -> second unique energy (let's call it `e2`)
        - `energies[0]` -> third unique energy (let's call it `e3`)
- **Expected Ordering**:
    - In the sorted list of unique energies, `e1` must be the smallest, followed by `e2`, and then `e3`.
- **Choice of Values**:
    - A simple set of values array can be created. We must ensure that:
        - The energy at index `3` is less than the energy at index `1` and both should be less than the energy at index `0`.

Let's select:
- `energies[3] = 1.0` (first unique, smallest value)
- `energies[1] = 3.0` (second unique, middle value)
- `energies[0] = 5.0` (third unique, largest value)

To ensure proper indexing and repetition, we can fill the rest of the list with duplicates of such values, for instance:
```python
energies = [5.0, 3.0, 5.0, 1.0]
```
With this arrangement, we maintain the index mapping:
- `5.0` at index `0` (first occurrence),
- `3.0` at index `1` (first occurrence),
- `1.0` at index `3` (first occurrence).

[/MONOLOGUE]
[ANSWER]
assert unique_sorted_indices([5.0, 3.0, 5.0, 1.0]) == [3, 1, 0]
[/ANSWER]

H   Task-specific Prefix

We append task-specific prefixes to the training samples to guide the model to perform different types of semantic reasoning.

Task: Natural Language to Code

Prefix:

```
    """
     You are an exceptionally intelligent coding assistant that consistently delivers
    accurate and reliable <Code> according to <NL_Description>

    <NL_Description>
    {prompt}

    <Code>
    {completion}
    """
```

Task: Forward Monologue

Prefix:

```
    """
    Simulate the Execution: You are given a Python function and an assertion containing a
    function input. Complete the assertion containing the execution output corresponding to
    the given input in [ANSWER] and [/ANSWER] tags.
    {prompt}
    {completion}
    """
```

Task: Forward Monologue

Prefix:

```
    """
    Deduce the Semantic Constraints: You are given a Python program and its expected output.
    Find one input such that executing the program with the input leads to the given output.
    Complete the assertion with one such input in between [ANSWER] and [/ANSWER].
    {prompt}
    {completion}
    """
```

Task: Debug and Self-refine

Prefix:

```
    """Debug and Refine the Code: You are given a a problem to be implemented in Python, and
    a buggy code that tries to solve the problem but fails the test case.
    You should firstly simulate the execution with the buggy code and the failed test to
    identify the root cause of the failure.
    Then, you should fix the bug and wrap the refined code in between [Refined] and [/Refined
    ].
    {instruction}
    {response}
    """
```

I Baseline Trace Formats

We present the baseline traces formats as we discussed and compared in Section 6.2.

Source Code and Test Case

```python
from typing import List # [L2]


def unique_sorted_indices(energies: List[float]) -> List[int]: # [L5]
    energy_dict = {}    # [L6]
    for idx, energy in enumerate(energies): # [L7]
        energy_dict.setdefault(energy, idx) # [L8]
    sorted_unique_energies = sorted(set(energies))  # [L9]
    unique_sorted_indices = [energy_dict[energy] for energy in sorted_unique_energies] #
[L10]
    return unique_sorted_indices # [L11]

assert unique_sorted_indices([10.5, 8.2, 10.5, 7.1, 8.2]) == [3, 1, 0] # [L13]
"""
```

Scratchpad

```
from typing import List

def unique_sorted_indices(energies: List[float]) -> List[int]: # [INPUT] {"energies":
[10.5, 8.2, 10.5, 7.1, 8.2]} [/INPUT]
    energy_dict = {}    # [STATE] {"energy_dict": {}} [/STATE]
    for idx, energy in enumerate(energies): # [STATE] {"idx": 0, "energy": 10.5} [/STATE
][STATE] {"idx": 1, "energy": 8.2} [/STATE][STATE] {"idx": 2, "energy": 10.5} [/STATE][
STATE] {"idx": 3, "energy": 7.1} [/STATE][STATE] {"idx": 4, "energy": 8.2} [/STATE]
        energy_dict.setdefault(energy, idx) # [STATE] {"energy_dict": "{10.5: 0}"} [/
STATE][STATE] {"energy_dict": "{10.5: 0, 8.2: 1}"} [/STATE][STATE] {"energy_dict":
"{10.5: 0, 8.2: 1, 7.1: 3}"} [/STATE]
    sorted_unique_energies = sorted(set(energies))  # [STATE] {"sorted_unique_energies":
[7.1, 8.2, 10.5]} [/STATE]
    unique_sorted_indices = [energy_dict[energy] for energy in sorted_unique_energies] #
[STATE] {"unique_sorted_indices": [3, 1, 0]} [/STATE]
    return unique_sorted_indices # [OUTPUT] [3, 1, 0] [/OUTPUT]
```

NeXT Scratchpad

```
from typing import List

def unique_sorted_indices(energies: List[float]) -> List[int]: # [INPUT] {"energies":
[10.5, 8.2, 10.5, 7.1, 8.2]} [/INPUT]
    energy_dict = {}    # [STATE-0] {"energy_dict": {}} [/STATE-0]
    for idx, energy in enumerate(energies): # [STATE-1] {"idx": 0, "energy": 10.5} [/
STATE-1][STATE-3] {"idx": 1, "energy": 8.2} [/STATE-3] ... [STATE-8] {"idx": 4, "energy":
 8.2} [/STATE-8]
        energy_dict.setdefault(energy, idx) # [STATE-2] {"energy_dict": "{10.5: 0}"} [/
STATE-2][STATE-4] {"energy_dict": "{10.5: 0, 8.2: 1}"} [/STATE-4][STATE-7] {"energy_dict
": "{10.5: 0, 8.2: 1, 7.1: 3}"} [/STATE-7]
    sorted_unique_energies = sorted(set(energies))  # [STATE-9] {"sorted_unique_energies
": [7.1, 8.2, 10.5]} [/STATE-9]
    unique_sorted_indices = [energy_dict[energy] for energy in sorted_unique_energies] #
[STATE-10] {"unique_sorted_indices": [3, 1, 0]} [/STATE-10]
    return unique_sorted_indices # [OUTPUT] [3, 1, 0] [/OUTPUT]
```

Concise Trace

```
"""
[L5] [INPUT] {"energies": [10.5, 8.2, 10.5, 7.1, 8.2]} [/INPUT] [/L5]
[L6] {"energy_dict": {}} [/L6]
[L7] {"idx": 0, "energy": 10.5} [/L7]
[L8] {"energy_dict": "{10.5: 0}"} [/L8]
[L7] {"idx": 1, "energy": 8.2} [/L7]
[L8] {"energy_dict": "{10.5: 0, 8.2: 1}"} [/L8]
[L7] {"idx": 2, "energy": 10.5} [/L7]
[L8] [/L8]
[L7] {"idx": 3, "energy": 7.1} [/L7]
[L8] {"energy_dict": "{10.5: 0, 8.2: 1, 7.1: 3}"} [/L8]
[L7] {"idx": 4, "energy": 8.2} [/L7]
[L8] [/L8]
[L7] [/L7]
[L9] {"sorted_unique_energies": [7.1, 8.2, 10.5]} [/L9]
[L10] {"unique_sorted_indices": [3, 1, 0]} [/L10]
[L11] [OUTPUT] [3, 1, 0] [/OUTPUT] [/L11]
"""
```

NeurIPS Paper Checklist

The checklist is designed to encourage best practices for responsible machine learning research, addressing issues of reproducibility, transparency, research ethics, and societal impact. Do not remove the checklist: **The papers not including the checklist will be desk rejected.** The checklist should follow the references and follow the (optional) supplemental material. The checklist does NOT count towards the page limit.

Please read the checklist guidelines carefully for information on how to answer these questions. For each question in the checklist:

- You should answer [Yes] , [No] , or [NA] .
- [NA] means either that the question is Not Applicable for that particular paper or the relevant information is Not Available.
- Please provide a short (1–2 sentence) justification right after your answer (even for NA).

The checklist answers are an integral part of your paper submission. They are visible to the reviewers, area chairs, senior area chairs, and ethics reviewers. You will be asked to also include it (after eventual revisions) with the final version of your paper, and its final version will be published with the paper.

The reviewers of your paper will be asked to use the checklist as one of the factors in their evaluation. While "[Yes] " is generally preferable to "[No] ", it is perfectly acceptable to answer "[No] " provided a proper justification is given (e.g., "error bars are not reported because it would be too computationally expensive" or "we were unable to find the license for the dataset we used"). In general, answering "[No] " or "[NA] " is not grounds for rejection. While the questions are phrased in a binary way, we acknowledge that the true answer is often more nuanced, so please just use your best judgment and write a justification to elaborate. All supporting evidence can appear either in the main paper or the supplemental material, provided in appendix. If you answer [Yes] to a question, in the justification please point to the section(s) where related material for the question can be found.

IMPORTANT, please:

- **Delete this instruction block, but keep the section heading "NeurIPS paper checklist",**
- **Keep the checklist subsection headings, questions/answers and guidelines below.**
- **Do not modify the questions and only use the provided macros for your answers**.

1. **Claims**

    Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

    Answer: [Yes]

    Justification: The summarization of the paper's contribution and novelty is in Abstract and Introduction (Section 1)

    Guidelines:

    - The answer NA means that the abstract and introduction do not include the claims made in the paper.
    - The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
    - The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
    - It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. **Limitations**

    Question: Does the paper discuss the limitations of the work performed by the authors?

    Answer: [Yes]

Justification: Appendix A

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. **Theory Assumptions and Proofs**

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification: There are no theoretical results in this work since our results focus on empirically improving and evaluating Code LLMs.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. **Experimental Result Reproducibility**

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: We have explained the configuration of our implementation and configuration. We will also release the reproducible artifact publicly.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general. releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
  (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
  (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
  (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
  (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. **Open access to data and code**

   Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

   Answer: [Yes]

   Justification: Our data, code, and models are available at: `https://github.com/Anonymous-Code-Proj/SemCoder`.

   Guidelines:

   - The answer NA means that paper does not include experiments requiring code.
   - Please see the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
   - While we encourage the release of code and data, we understand that this might not be possible, so "No" is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
   - The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
   - The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
   - The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.

- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. **Experimental Setting/Details**

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: We include data collection and experimental configuration in Section 5.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. **Experiment Statistical Significance**

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [No]

Justification: We fine-tune a 6.7B transformer decoder model and use greedy decoding for our main results in Table 1. There's no need to report statistical significance.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. **Experiments Compute Resources**

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: In Section 5

Guidelines:

- The answer NA means that the paper does not include experiments.

- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. **Code Of Ethics**

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics `https://neurips.cc/public/EthicsGuidelines`?

Answer: [Yes]

Justification: We checked the code of ethics and ensure our research algins with the code.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. **Broader Impacts**

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: Appendix B

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. **Safeguards**

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [Yes]

Justification: Appendix B

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. **Licenses for existing assets**

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: Our data is synthesized by GPT-3.5, and we have explicitly mentioned that in the paper, and all related works we borrow ideas from are cited

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, `paperswithcode.com/datasets` has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New Assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [Yes]

Justification: Our documents will be available at `https://github.com/ARiSE-Lab/SemCoder`

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and Research with Human Subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA] .

Justification: There's no crowdsourcing nor human subjects in our paper.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional Review Board (IRB) Approvals or Equivalent for Research with Human Subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA] .

Justification: There's no crowdsourcing nor human subjects in our paper.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.