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Enhancing Code Generation via Bidirectional Comment-Level Mutual Grounding

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***Abstract*—Large Language Models (LLMs) have demonstrated unprecedented capability in code generation. However, LLM-generated code is still plagued with a wide range of functional errors, especially for complex programming tasks that LLMs have not seen before. Recent studies have shown that developers often struggle with inspecting and fixing incorrect code generated by LLMs, diminishing their productivity and trust in LLM-based code generation. Inspired by the mutual grounding theory in communication, we propose an interactive approach that leverages code comments as a medium for developers and LLMs to establish a shared understanding. Our approach facilitates iterative grounding by interleaving code generation, inline comment generation, and contextualized user feedback through editable comments to align generated code with developer intent. We evaluated our approach on two popular benchmarks and demonstrated that our approach significantly improved multiple state-of-the-art LLMs, e.g., 17.1% pass@1 improvement for code-davinci-002 on HumanEval. Furthermore, we conducted a user study with 12 participants in comparison to two baselines: (1) interacting with GitHub Copilot, and (2) interacting with a multi-step code generation paradigm called Multi-Turn Program Synthesis. Participants completed the given programming tasks 16.7% faster and with 10.5% improvement in task success rate when using our approach. Both results show that interactively refining code comments enables the collaborative establishment of mutual grounding, leading to more accurate code generation and higher developer confidence.**

***Index Terms*—LLM, Code Generation, Code Refinement**

I. Introduction

The quest for automated code generation, dating back to the 1960s [1], [2], has evolved significantly. This field has transitioned from early deductive program synthesis methods [3]–[6] to the recent advent of Large Language Models (LLMs) [7]–[9]. Despite the significant progress, LLMs often fail to align with developer intent due to factors such as reliance on spurious features, lack of user context, and misunderstanding of complex specifications [10]–[14]. Recent efforts to address these limitations include model fine-tuning [15], [16], new prompting strategies [17], [18], and iterative refinement paradigms [19], [20]. However, the improvement brought by these methods is still limited. For example, Self-Debug [19] only achieved a 4.8% pass@1 increase for Codex on MBPP when test execution feedback is not available.

Recent studies [11], [21], [22] highlight the critical role of bi-directional communication between developers and LLMs in programming tasks. While developers can edit prompts, LLMs often treat such edits as new prompts, hindering their ability to understand and incorporate developers' refinement intent. Conversational models like ChatGPT offer multi-turn dialogues for feedback. However, effectively encoding historical utterances and contextualizing feedback within conversations remains a complex and challenging task [23]–[26].

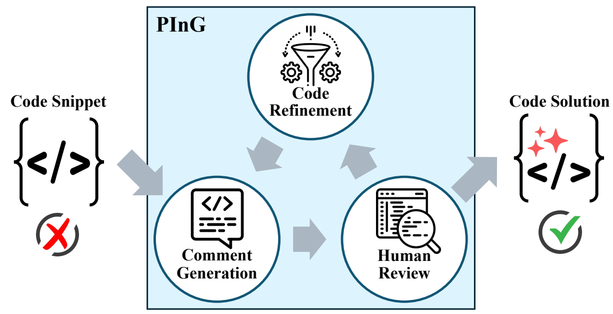


Fig. 1. Generating a code solution in our pipeline.

In this work, we propose a new interactive approach called Programming with Interactive Grounding (PING). Figure 1 illustrates this approach. PING employs inline comments as a medium for bi-directional communication between a developer and the model. This approach is inspired by the grounding theory in communication [27], which underscores the importance of mutual understanding in collaborative interactions. Unlike prior work that relies on coarse-grained code explanations for refinement [19], [28], PING's use of inline comments offers a more fine-grained approach. These comments directly address individual statements of the code, making it easier to target specific code segments for precise feedback and refinement.

Given a code snippet generated by an LLM, PING uses a code comment generation model to create inline comments that clarify each statement's behavior. These comments provide developers with an immediate, understandable code description, helping them quickly spot potential errors. Developers can edit the comments to specify the correct behavior for the erroneous statement. A code refinement model then regenerates the statement and subsequent segment identified by the feedback, rather than the entire code snippet.

Inline comments are essentially natural language descriptions, which are suitable for developers at all levels. This approach allows for more precise error identification compared to prompt editing or conversational models, which often require the model to infer the location of errors throughout the entire code snippet. Comment editing also directly indicates

[1]

[1] https://github.com/NecoraNyaru/PInG

Context c

```
def solve(N):
"""Given a positive integer N, return the total
sum of its binary digits in binary.
Example For N = 1000, the sum of digits will be
6 the output should be "110". For N = 150, the
sum of digits will be 4 the output should be
"100". For N = 147, the sum of digits will be 4
the output should be "100".
Variables: @N integer Constraints: 0 ≤ N ≤
10000.
Output: a string of binary number
"""
```

Code Snippet x

```
sum_of_digits = 0

digits = str(N)
for digit in digits:
    sum_of_digits += int(digit)

return bin(sum_of_digits)[2:]
```

1. Code Snippet with Comment $\dot{x}$

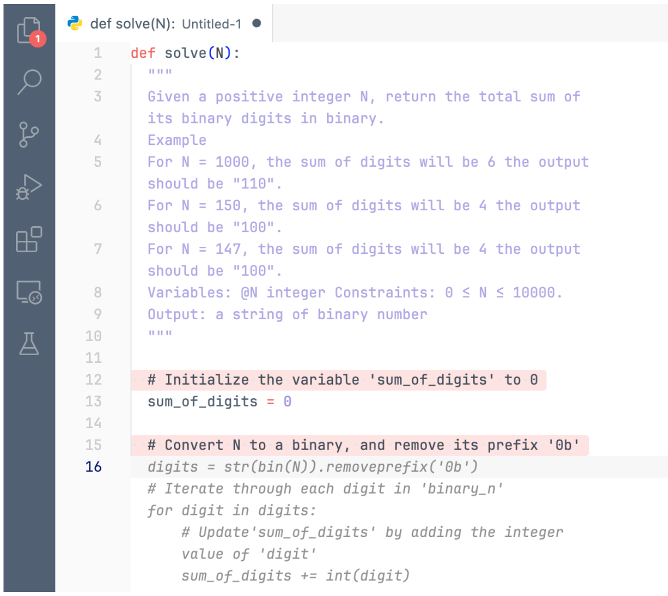
```
# Initialize the variable 'sum_of_digits' to 0
sum_of_digits = 0

# Convert N to a string
digits = str(N)
# Iterate through each digit in 'digits'
for digit in digits :
    # Update'sum_of_digits' by adding the integer
value of 'digit'
    sum_of_digits += int(digit)

# Convert the sum of digits to a binary, remove the
first two characters and return
return bin(sum_of_digits)[2:]
```

2. Refine the comment of the incorrect line of code

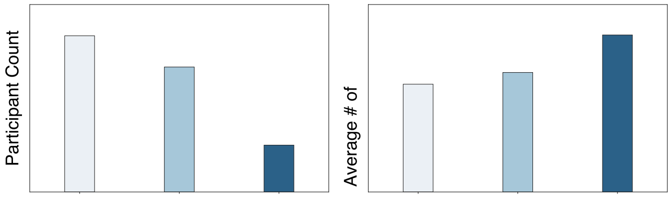
```
...
- # Convert N to a string
+ # Convert N to a binary, and remove its prefix '0b'
digits = str(N)
...
```

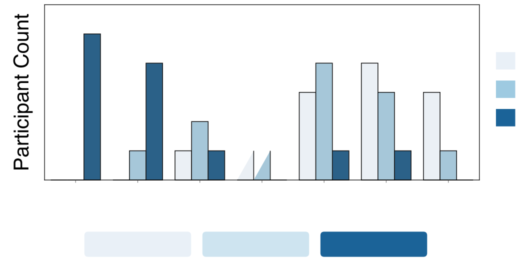
3. Regenerate based on the refined comment

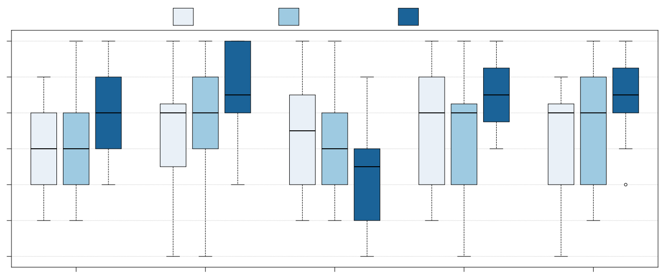
```
# Initialize the variable 'sum_of_digits'
to 0
sum_of_digits = 0

# Convert N to a binary and remove its
prefix '0b'
- digits = str(N)
+ digits = str(bin(N)).removeprefix('0b')
# Iterate through each digit in
'binary_n'
for digit in digits:
    # Update'sum_of_digits' by adding the
integer value of 'digit'
    sum_of_digits += int(digit)

# Convert the sum of digits to a binary,
remove the first two characters and
return
return bin(sum_of_digits)[2:]
```


def solve(N): Untitled-1
def solve(N):
"""
Given a positive integer N, return the total sum of its binary digits in binary.
Example
For N = 1000, the sum of digits will be 6 the output should be "110".
For N = 150, the sum of digits will be 4 the output should be "100".
For N = 147, the sum of digits will be 4 the output should be "100".
Variables: @N integer Constraints: 0 ≤ N ≤ 10000.
Output: a string of binary number
"""
# Initialize the variable 'sum_of_digits' to 0
sum_of_digits = 0
# Convert N to a binary, and remove its prefix '0b'
digits = str(bin(N)).removeprefix('0b')
# Iterate through each digit in 'binary_n'
for digit in digits:
# Update'sum_of_digits' by adding the integer value of 'digit'
sum_of_digits += int(digit)

(1)


Participant Count
Average # of


Participant Count



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