Large Language Models Are Not (Yet) Robust in Understanding Code Against Semantics-Preserving Mutations

Pedro Orvalho [1]*, and Marta Kwiatkowska [2]

[1] Institut d'Investigació en Intelligència Artificial (IIIA-CSIC), Barcelona, Catalonia, Spain
[2] Department of Computer Science, University of Oxford, Oxford, UK

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*PO is now at IIIA-CSIC. This work was carried out while he was at the University of Oxford.

Motivation

- The software engineering community has embraced LLM-based tools, such as GitHub Copilot and ChatGPT, to **streamline code workflows, assist in debugging, and even automate code completion**.

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- LLMs **are widely used, and often blindly**, with developers placing significant trust in their capabilities [Oh et al., 2024].

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- To what extent do LLMs **truly understand code and the underlying semantics of programs**?

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- If LLMs outputs are simply the result of statistical associations, then **their reliability in critical development tasks could be overestimated** [Gu et al., 2024].

- In other domains, such as mathematical competitions [Petrov et al., 2025], LLMs tend to **provide accurate predictions, but based on flawed reasoning**.

Motivation

```
1  def minPossibleSum(n:int, target:int)->int:
2      i = 1
3      arr = {1}
4      while len(arr) < n:
5          i += 1
6          if target - i not in arr:
7              arr.add(i)
8      return sum(arr)
```

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Given two integers `n` and `target`, function `minPossibleSum` finds the sum of an array `arr` such that:

- `len(arr) == n`;
- all elements in `arr` are distinct positive integers;
- $\nexists_0^{n-1}(i,j) : arr[i] + arr[j] == target$;

Motivation

```python
def minPossibleSum(n:int, target:int)->int:
    i = 1
    arr = {1}
    while len(arr) < n:
        i += 1
        if target - i not in arr:
            arr.add(i)
    return sum(arr)
assert minPossibleSum(n=1,target=1)==???
```

LLMs for code (LLMCs)

Imagine we ask QWEN2.5-CODER, to predict this function's output, and to explain its reasoning.

Qwen2.5-Coder's Answer

Let's walk through the execution of the code step-by-step to understand how the output is produced.

The function `minPossibleSum` takes two parameters: `n` and `target`. In this case, `n = 1` and `target = 1`.

1. The variable `i` is initialized to 1.
2. A set `arr` is initialized with the element 1.
3. The while loop condition checks if the length of `arr` is less than `n`.
Since `n` is 1, the loop will run once.
4. Inside the loop, `i` is incremented to 2.

```python
def minPossibleSum(n, target):
    i = 1
    arr = {1}
    while len(arr) < n:
        i += 1
        if target - i not in arr:
            arr.add(i)
    return sum(arr)
assert minPossibleSum(n=1,target=1)==???
```

Qwen2.5-Coder's Answer

5. The condition `if target - i not in arr` is checked. Here, `target - i` is `1 - 2`, which equals `-1`.
Since `-1` is not in the set `arr`, the condition is true.
6. The number 2 is added to the set `arr`.
7. The loop ends because the length of `arr` is now `n`.
8. The function returns the sum of the elements in `arr`, which is `1 + 2 = 3`.
Therefore, the assertion should be:
[ANSWER]assert minPossibleSum(1, 1) == 3[/ANSWER]

```python
def minPossibleSum(n, target):
    i = 1
    arr = {1}
    while len(arr) < n:
        i += 1
        if target - i not in arr:
            arr.add(i)
    return sum(arr)
assert minPossibleSum(n=1,target=1)==???
```

Providing some feedback to Qwen2.5-Coder

```
Your previous output prediction was INCORRECT!
Try again. Complete the initial program
assertion containing the execution output
corresponding to the given input in [ANSWER]
and [/ANSWER] tags.
For example, the answer to
'''assert sumEvenNumbers([1,2,3,4])==???'''
would be
[ANSWER]
assert sumEvenNumbers([1,2,3,4]) == 6
[/ANSWER]
Please complete the assertion and explain
your reasoning for your new prediction,
using no more than 1000 tokens.
```

Qwen2.5-Coder's Answer

There seems to be a misunderstanding in the explanation. Let's re-evaluate the logic:
- Initially, `arr` contains {1}
- The loop runs while the length of `arr` is less than `n`.
- In each iteration, `i` is incremented, and if `target - i` is not in `arr`, `i` is added to `arr`.

Given `n = 1` and `target = 1`:
- Initially, `arr = 1`.
- The loop does not run because `len(arr) < n` (1 < 1) is false.
- Therefore, the loop does not add any new elements to `arr`. Thus, the final `arr` remains `1`, and the sum is `1`.

Therefore, the correct assertion should be:
[ANSWER]assert minPossibleSum(1, 1) == 1[/ANSWER]

Qwen2.5-Coder's Answer

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elements to `arr`. Thus, the final `arr`
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Therefore, the correct assertion should be:
[ANSWER]assert minPossibleSum(1, 1) == 1[/ANSWER]
```

Our feedback was sufficient to **guide Qwen2.5-Coder toward a logically sound reasoning process and to correctly predict the output**!

LLMs' Robustness

LLMs for code (LLMCs)

- When GPT-5.2 and GEMINI-3 are presented with this semantically equivalent function, **both models fail to provide the correct output**;

```python
def minPossibleSum(n, target):
    i = 1
    eAJMfVcq = {1}
    while len(eAJMfVcq) < n:
        i += 1
        if target - i not in eAJMfVcq:
            eAJMfVcq.add(i)
    return sum(eAJMfVcq)
```

LLMs' Robustness

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- When GPT-5.2 and GEMINI-3 are presented with this semantically equivalent function, **both models fail to provide the correct output**;
- Both models also **fail to construct logically sound reasoning**.

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In this work

- Conduct a **manual expert evaluation to assess whether LLMs' code output predictions** are based on logically sound reasoning, flawed reasoning, or mere guesses.

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- Evaluate LLMs' **output prediction stability** across five different semantics-preserving code mutations.

Semantics-Preserving Code Mutation

Given a program P that is **syntactically well-formed program**, and it is **semantically consistent with the test suite**, i.e.,

$$\forall (t_{in}^{i}, t_{out}^{i}) \in T \ : \ P(t_{in}^{i}) = t_{out}^{i}.$$

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and P_m is **syntactically well-formed** and **semantically consistent with the original specification**:

$$\forall(t^i_{in}, t^i_{out}) \in T \ : \ P_m(t^i_{in}) = t^i_{out}.$$

Semantics-Preserving Code Mutations

We introduce **five semantics-preserving code mutations** designed to syntactically modify Python programs without altering their semantics:

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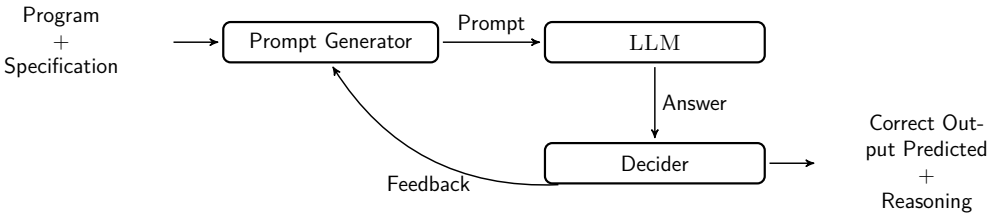
We introduce **five semantics-preserving code mutations** designed to syntactically modify Python programs without altering their semantics:

- variable renaming;
- comparison expression mirroring;
- swapping if-else statements;
- loop conversion
- partial loop unrolling.

LLM-Based Program Output Prediction



Experimental Setup

- **Evaluation Benchmarks:**
  - LiveCodeBench [Jain et al., 2024] **contains 479 programs** submitted to programming contests across competition platforms, such as LeetCode;
  - CruxEval [Gu et al., 2024] **contains 800 functions** generated by CodeLlama, each accompanied by a set of input-output examples for evaluation.

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- For each program mutation, **we generate a separate transformed version of the benchmark**, each program containing at most one mutation;
- We also **check that the semantics of the original program is preserved** in the mutated versions.

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    - IBM's GraniteCode;
    - Google's CodeGemma;
    - Mistral's Mistral;
    - SemCoder;
    - Alibaba's Qwen3-Coder;
    - OpenAI's GPT-5.2;
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  - **The other model is a general-purpose LLM**: Meta's Llama3;
- Experiments were conducted using a timeout of **90s**.

Analysis of LLMs' Reasoning About Code

LLMs	CodeGemma	GraniteCode	Qwen3-Coder	Mistral	SemCoder	Llama3	GPT-5.2	Gemini-3
%Failed Predictions	66.8	65.1	49.5	67.4	52.0	61.4	2.5	0.0
%Correct Predictions	33.2	34.9	50.5	32.6	48.0	38.6	97.5	100.0

Expert Analysis of LLMs' Reasoning About Code

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%Correct Predictions	33.2	34.9	50.5	32.6	48.0	38.6	97.5	100.0
%Correct Guesses based on flawed reasoning	44.7	43.1	3.0	50.0	16.1	55.1	0.2	0.2
%Correct Predictions based on sound reasoning (>1 iteration)	3.8	13.8	1.6	–	–	18.9	8.6	0.0
%Correct Predictions based on sound reasoning (=1 iteration)	51.6	43.1	95.4	50.0	83.9	25.9	91.2	99.8

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RQ1. Are Large Language Models (LLMs) truly reasoning about code semantics, or merely guessing likely answers?

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RQ2. Does the interactive querying process help LLMs arrive at correct predictions supported by logically sound reasoning?

Robustness to Semantics-Preserving Mutations

LiveCodeBench

LLMs	Original Code	Loop Conversion	Expression Mirroring	Variable Renaming	Swap If-Else	Loop Unrolling
CodeGemma	33.2%	26.3 (-6.9)	31.7 (-1.5)	38.0 (+4.8)	28.4 (-4.8)	10.9 (-22.3)
GraniteCode	34.9%	27.1 (-7.7)	31.3 (-3.5)	38.8 (+4.0)	29.2 (-5.6)	8.4 (-26.5)
Llama3	38.6%	34.4 (-4.2)	34.2 (-4.4)	46.8 (+8.1)	30.1 (-8.6)	9.4 (-29.2)
Mistral	32.6%	24.0 (-8.6)	29.2 (-3.3)	38.2 (+5.6)	27.1 (-5.4)	10.4 (-22.1)
Qwen3-Coder	50.5%	37.8 (-12.7)	44.1 (-6.5)	54.7 (+4.2)	33.2 (-17.3)	15.4 (-35.1)
SemCoder	48.0%	40.1 (-7.9)	48.9 (+0.8)	62.4 (+14.4)	40.3 (-7.7)	15.2 (-32.8)
GPT-5.2	97.1%	**72.4 (-24.6)**	81.0 (-16.1)	98.5 (+1.5)	78.3 (-18.8)	29.0 (-68.1)
Gemini-3	100.0%	**55.3 (-44.7)**	76.0 (-24.0)	68.1 (-31.9)	71.4 (-28.6)	29.6 (-70.4)

Table 1: Output prediction correction rate of each LLM on LiveCodeBench when applying different code mutations: converting for to while loops (F2W), mirroring comparison expressions (MCE), renaming variables (RV), swap if-else statements (SIE), and unroll loops (UL).

Robustness to Semantics-Preserving Mutations

CruxEval

LLMs	Original Code	Loop Conversion	Expression Mirroring	Variable Renaming	Swap If-Else	Loop Unrolling
CodeGemma	30.9%	15.8 (-15.1)	17.6 (-13.3)	34.9 (+4.0)	20.1 (-10.8)	8.9 (-22.0)
GraniteCode	32.6%	14.2 (-18.4)	17.1 (-15.5)	35.4 (+2.8)	19.8 (-12.9)	8.1 (-24.5)
Llama3	26.5%	15.0 (-11.5)	17.4 (-9.1)	37.5 (+11.0)	19.2 (-7.2)	6.6 (-19.9)
Mistral	23.8%	11.0 (-12.8)	13.4 (-10.4)	25.5 (+1.8)	13.9 (-9.9)	6.5 (-17.2)
Qwen3-Coder	48.9%	23.1 (-25.8)	26.2 (-22.6)	49.9 (+1.0)	26.2 (-22.6)	12.5 (-36.4)
SemCoder	50.6%	25.2 (-25.4)	29.9 (-20.8)	55.8 (+5.1)	30.4 (-20.2)	12.8 (-37.9)
GPT-5.2	86.0%	**42.2 (-43.8)**	47.9 (-38.1)	87.0 (+1.0)	52.9 (-33.1)	23.0 (-63.0)
Gemini-3	76.8%	**29.1 (-47.6)**	50.9 (-25.9)	66.2 (-10.5)	41.2 (-35.5)	24.4 (-52.4)

Table 2: Output prediction correction rate of each LLM on CruxEval when applying different code mutations: converting for to while loops (F2W), mirroring comparison expressions (MCE), renaming variables (RV), swap if-else statements (SIE), and unroll loops (UL).

Robustness to Semantics-Preserving Mutations

RQ3. Do different code mutations lead LLMs to produce different predictions for the same program?

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- **It is crucial to analyse the set of distinct output predictions** generated under different mutations to assess the stability of each LLM.

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RQ3. Do different code mutations lead LLMs to produce different predictions for the same program?

- **It is crucial to analyse the set of distinct output predictions** generated under different mutations to assess the stability of each LLM.
- This allows us to **determine whether the models maintain consistent reasoning and predictions** across semantically equivalent program variants.

Robustness to Semantics-Preserving Mutations

LiveCodeBench

LLMs	Original Benchmark	Original + F2W	Original + MCE	Original + RV	Original + SIE	Original + UL	Original + All Mutations
CodeGemma	33.2%	5.8%	8.4%	10.2%	6.5%	1.9%	18.0%
GraniteCode	34.9%	3.5%	4.0%	6.3%	4.2%	0.4%	10.4%
Llama3	38.6%	12.3%	11.3%	16.5%	10.0%	2.5%	26.9%
Mistral	32.6%	3.1%	3.3%	7.5%	3.8%	1.7%	11.5%
Qwen3-Coder	50.5%	7.5%	7.5%	10.2%	6.3%	2.3%	14.8%
SemCoder	48.0%	15.0%	18.6%	23.6%	14.8%	4.0%	36.5%
GPT-5.2	97.1%	1.0%	0.8%	2.1%	1.3%	0.4%	2.7%
Gemini-3	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Table 3: Output prediction stability of LLMs on LiveCodeBench when running a portfolio approach, applying different code mutations: converting for to while loops (F2W), mirroring comparison expressions (MCE), renaming variables (RV), swap if-else statements (SIE), and unroll loops (UL).

Robustness to Semantics-Preserving Mutations

CruxEval

LLMs	Original Benchmark	Original + F2W	Original + MCE	Original + RV	Original + SIE	Original + UL	Original + All Mutations
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GraniteCode	32.6%	1.6%	1.5%	5.9%	2.2%	0.6%	7.9%
Llama3	26.5%	4.9%	5.0%	16.0%	6.8%	1.6%	21.4%
Mistral	23.8%	0.9%	1.5%	4.5%	2.2%	0.2%	6.6%
Qwen3-Coder	48.9%	1.5%	1.6%	5.0%	2.5%	0.6%	6.4%
SemCoder	50.6%	4.6%	5.1%	11.1%	6.0%	1.6%	14.9%
GPT-5.2	86.0%	1.9%	1.5%	3.6%	2.2%	0.8%	4.6%
Gemini-3	76.8%	6.8%	7.4%	14.4%	1.8%	3.4%	15.5%

Table 4: Output prediction stability of LLMs on CruxEval when running a portfolio approach, applying different code mutations: converting for to while loops (F2W), mirroring comparison expressions (MCE), renaming variables (RV), swap if-else statements (SIE), and unroll loops (UL).

Robustness to Semantics-Preserving Mutations

RQ4. Are LLMs robust in understanding code against semantics-preserving mutations?

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LLMs	LiveCodeBench + Mutations	CruxEval + Mutations
CodeGemma	51.2 (+18.0)	42.3 (+11.4)
GraniteCode	45.3 (+10.4)	40.5 (+7.9)
Llama3	65.5 (+26.9)	47.9 (+21.4)
Mistral	44.1 (+11.5)	30.4 (+6.6)
Qwen3-Coder	65.3 (+14.8)	55.3 (+6.4)
SemCoder	84.5 (+36.5)	65.5 (+14.9)
GPT-5.2	99.8 (+2.7)	90.6 (+4.6)
Gemini-3	100.0 (+0.0)	92.3 (+15.5)

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    - e.g., CodeGemma and Mistral achieve correct answers in 32-39% of the cases, yet **50% of those are not grounded in valid semantic reasoning**.
  - LLMs often change predictions in response to our code mutations, indicating **limited robustness in their semantic understanding**.

Thank you

Questions?

Pedro Orvalho, and Marta Kwiatkowska. **Large Language Models Are Not (Yet) Robust in Understanding Code Against Semantics-Preserving Mutations**. EPIA 2026.

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Appendix

Variable renaming

```python
def f(nums):
  sum = 0
  for n in nums:
    if n % 2 == 0:
      sum += n
    else:
      sum += 0
  return sum
```

```python
def f(nums):
  uoWIfiQc = 0
  for n in nums:
    if n % 2 == 0:
      uoWIfiQc += n
    else:
      uoWIfiQc += 0
  return uoWIfiQc
```

Comparison Expression Mirroring

```python
def f(nums):
  sum = 0
  for n in nums:
    if n % 2 == 0:
      sum += n
    else:
      sum += 0
  return sum
```

```python
def f(nums):
  sum = 0
  for n in nums:
    if 0 == n % 2:
      sum += n
    else:
      sum += 0
  return sum
```

Swap If-Else Statements

```
def f(nums):
  sum = 0
  for n in nums:
    if n % 2 == 0:
      sum += n
    else:
      sum += 0
  return sum
```

```
def f(nums):
  sum = 0
  for n in nums:
    if not n % 2 == 0:
      sum += 0
    else:
      sum += n
  return sum
```

For-to-While Loop Conversion

```python
def f(nums):
    sum = 0
    for n in nums:
        if n % 2 == 0:
            sum += n
        else:
            sum += 0
    return sum
```

```python
def f(nums):
    sum = 0
    i = 0
    while i < len(nums):
        n = nums[i]
        if n % 2 == 0:
            sum += n
        else:
            sum += 0
        i += 1
    return sum
```

Partial Loop Unrolling

```python
def f(nums):
  sum = 0
  i = 0
  while i < len(nums):
    n = nums[i]
    if n % 2 == 0:
      sum += n
    else:
      sum += 0
    i += 1
  return sum
```

```python
def f(nums):
  sum, i = 0, 0
  while i < (len(nums)-1):
    n = nums[i]
    if n % 2 == 0:
      sum += n
    else:
      sum += 0
    i += 1
  if len(nums) > i:
    n = nums[i]
    if n % 2 == 0:
      sum += n
    else:
      sum += 0
    i += 1
  return sum
```

Prompt Example

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.

For example, the answer to
'''assert sumEvenNumbers([1,2,3,4])==???'''
would be
[ANSWER]
assert sumEvenNumbers([1,2,3,4]) == 6
[/ANSWER]

Please complete the assertion and explain your reasoning for your prediction, using no more than 1000 tokens.

```python
def f(nums):
    # python function
assert f([1, 2, 3, 4, 5]) == ???
```

Prompt Example for Feedback

```
Your previous output prediction was INCORRECT!
Try again. Complete the initial program
assertion containing the execution output
corresponding to the given input in [ANSWER]
and [/ANSWER] tags.
For example, the answer to
'''assert sumEvenNumbers([1,2,3,4])==???'''
would be
[ANSWER]
assert sumEvenNumbers([1,2,3,4]) == 6
[/ANSWER]
```

```
Please complete the assertion
and explain your reasoning for
your new prediction, using no
more than 1000 tokens.

```python
def f(nums):
    # python function
assert f([1, 2, 3, 4, 5]) == ???
```
```