User-intent formalization problem for programs

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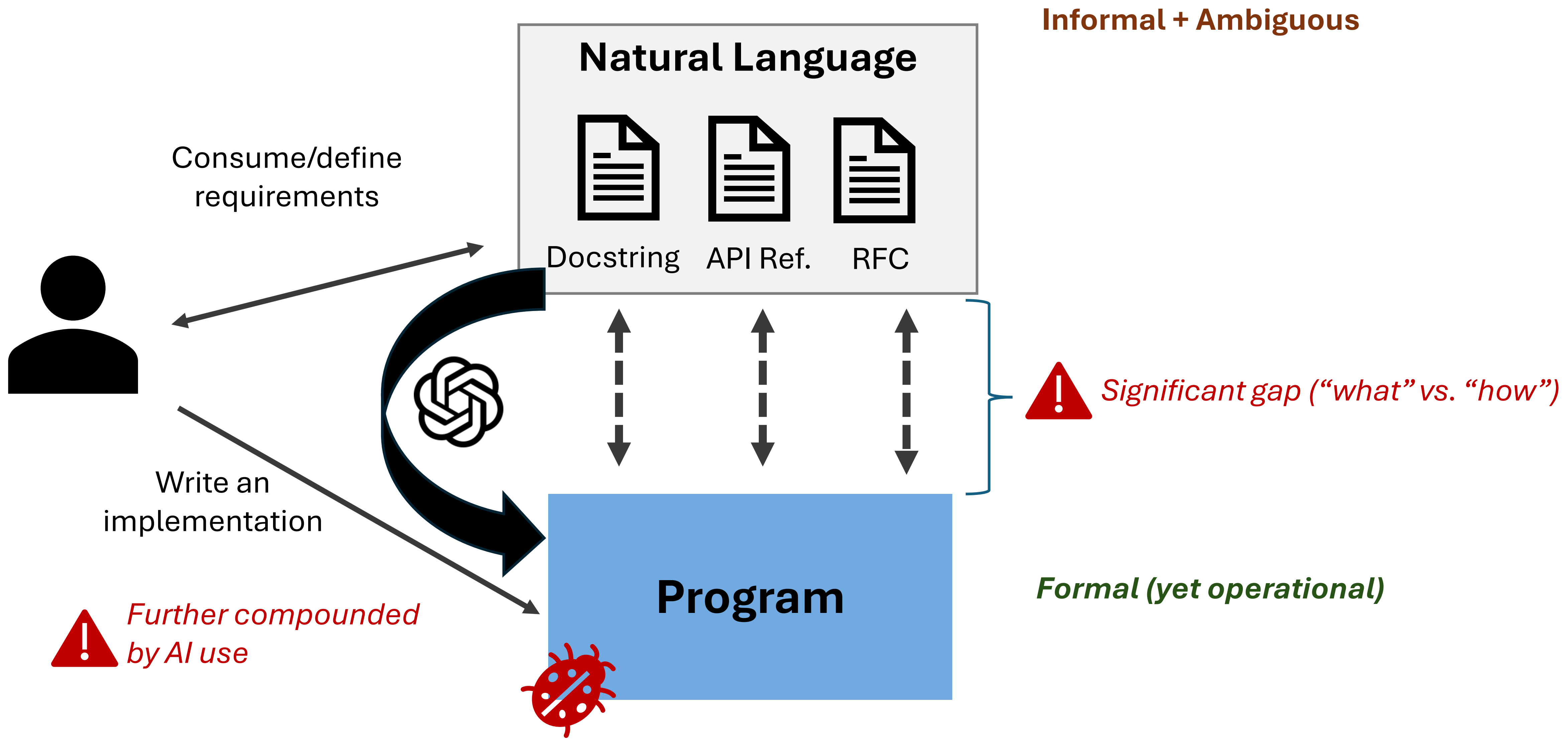
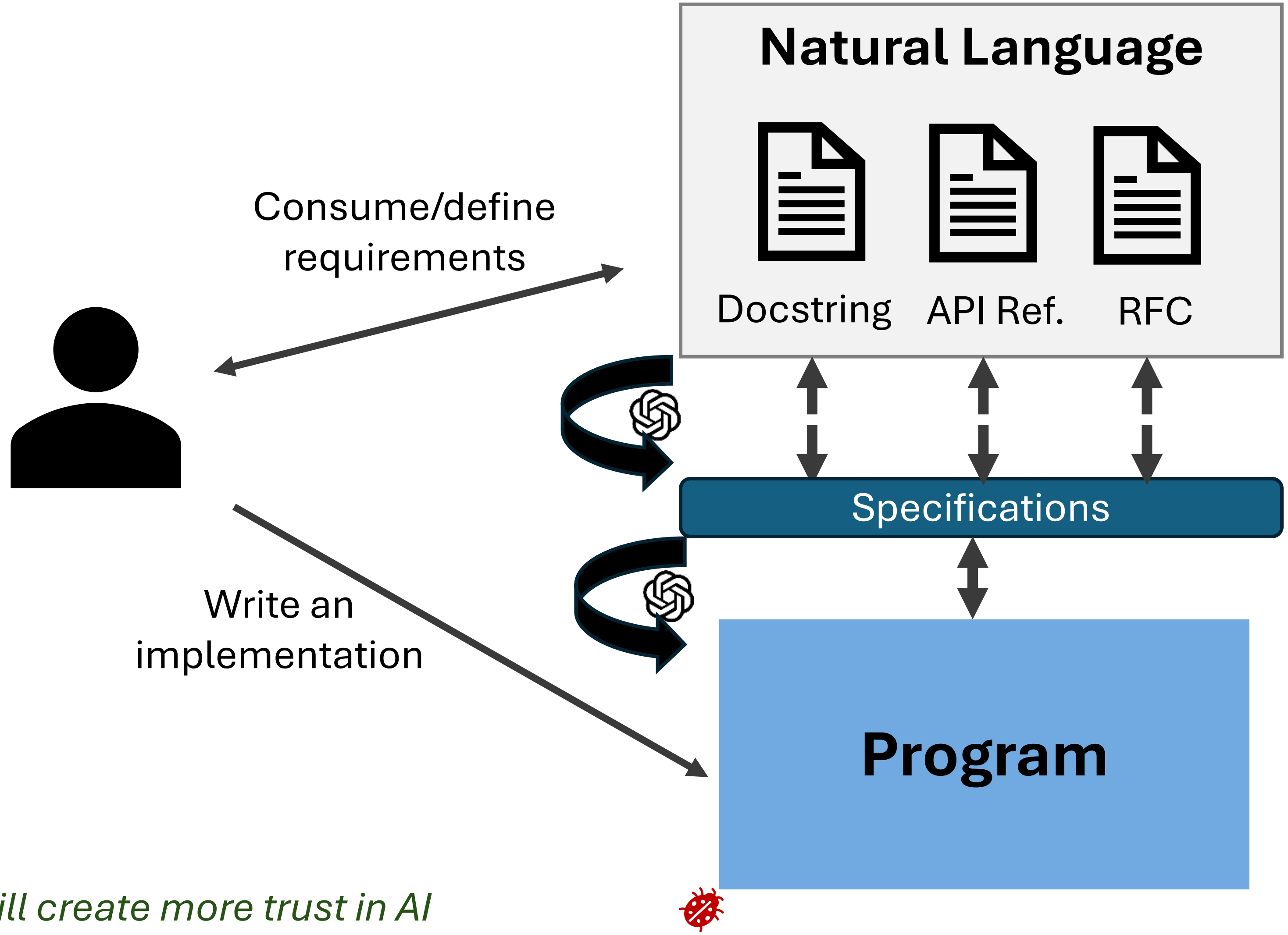
Trusted AI-assisted Programming

Software requirements are often specified informally



Vision: Formal specifications can reduce the gap



Informal + Ambiguous

⚠Smaller gap (both capture "what")

Formal (declarative)

Enforceable by PL methods (tests, formal verification, refinement)

Formal (yet operational)

Will create more trust in AI generated code

[*Interactive Code Generation via Test-Driven User-Intent Formalization*. Lahiri, Fakhoury et al., arXiv:2208.05950]

User-intent formalization (UIF) for programs

- Problem
  - Evaluate the quality of (LLM-generated) formal specification given informal artefacts
    - Natural language + code (interpreted neurally)
    - Like “autoformalization” problem for math theorems, but crucial differences
      - [*Autoformalization with Large Language Models*, Wu et al. NeurIPS’22]
  - Input can optionally contain formal artefacts such as tests/specs etc.

- Challenge: Not a pure Programming Languages (PL) problem

- Solution:
  - Adopt the approach of machine learning (ML) folks of establishing benchmarks (examples and {automated, objective} metrics)
  - Make the **metrics PL based** (like nl2code generation)

User-intent formalism (UIF) for different programming languages

- UIF for **mainstream languages** (Python, Java), and use case
  - Endres, Fakhoury, Chakraborty, Lahiri *FSE'24*
- UIF for **verification-aware languages** (Dafny, F*, Verus, …)
  - Lahiri (in preparation)

This talk

- UIF for **effectively analyzable symbolic languages** (EASL)
  - 3DGen: Fakhoury, Kuppe, Lahiri, Ramananandro, Swamy
  - vectorizeGPT: Taneja, Yan, Lahiri (in preparation)

Lightning talks

UIF for **mainstream languages** (Python, Java)

Can Large Language Models Transform Natural Language Intent into Formal Method Postconditions? Endres, Fakhoury, Chakraborty, Lahiri *FSE'24*

UIF for **mainstream languages** (Python, Java)

[1,2,3,2,4] -> [1,3,4]

```python
def remove_duplicates(numbers: List[int]):
    """ From a list of integers, remove all elements that occur more than once,
        Keep order of elements left the same as in input."""
```

Formal Specifications in Python

```python
assert len(set(numbers)) == len(set(return_list))
```

```python
assert all(numbers.count(i) == 1 for i in return_list)
```

```python
assert all(i in return_list for i in numbers if numbers.count(i) == 1)
```

Problem formulation and evaluation metrics

- Given
  - NL description nl for a method m
  - Hidden tests T and hidden reference implementation I
- Generate a postcondition S of m from nl
- Evaluation metrics
  - **Test-set Soundness**: S passes on I for all the tests in T
  - **Bug Completeness**: S discriminates against buggy implementations {I'}
    - Inspired by mutation-testing
    - **Insight**: Generate list of buggy I' by sampling LLM responses given nl and evaluating using T

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RQ1: Evaluation on basic Python programs

- Dataset: **EvalPlus** (HumanEval + extensive test suite)
  - [*Is Your Code Generated by ChatGPT Really Correct? Rigorous Evaluation of Large Language Models for Code Generation*. Liu et al. NeurIPS'23]
- Models: GPT-3.5, GPT-4 and open source StarCoder

- Takeaways:
  - GPT-4 significantly better at producing test-set sound (~96% in 10 tries) and complete (~62% in 10 tries) specifications
  - Much more pronounced for completeness since `assert True` and `assert isinstance(return_list, list)` are sound but not discriminatory
  - The metrics correlate strongly with the result of manual labeling (by authors) of the generated specifications in most cases
  - Challenge: need to rank specifications in increasing order of completeness for practical usage

RQ2: Can GPT-4 generated specifications find real-world bugs?

- Experimental setup with Defects4J [Just, Jalali, Ernst. ISSTA 2014]
  - Given two versions of a code: B (buggy), F (fixed)
  - Prompted LLMs to generate a postcondition S given B
  - Bug-discriminating postcondition
    - Check if S fails B and succeeds F for some test t in provided test suite T

- GPT-4 found 47 bug-discriminating postcondition of the 525 bugs analyzed
  - Complementary to prior assertion generation approaches TOGA [Dinella, Ryan, Mytkowicz, Lahiri, ICSE'22] and Daikon [Ernst et al. ICSE'99]
    - TOGA mostly finds expected exceptional bugs. TOGA can only tolerate bugs during testing, and cannot prevent bugs in production.
    - Daikon specs overfit the regression tests and bug-discriminating specs are unsound

UIF for **verification-aware languages**
(Dafny, F*, Verus, …)

Challenge

- Earlier approached do not readily apply
  - Specifications contain ghost variables and complex quantifiers (cannot be evaluated using dynamic methods)
  - Trying to verify specification against reference implementation would likely not be automated (intermediate lemmas and invariants)

- Our approach: symbolically test specifications (given tests as input/output examples)
  - Given
    - A method signature
      `method Foo(x): (returns y) requires P(x) ensures Q(x, y)`
    - A set of input/output tests T
  - **Specification Soundness** (for a test (i, o)) //Boolean metric
    - `{P} x := i; y := o; {Q}` is valid
  - **Specification Completeness** (for a test (i,o)) //Quantitative metric
    - Fraction of mutants o’ of o, s.t. `{P} x := i; y := o’; {Q}` is not valid

Evaluation (**preliminary**)

- Dataset: ~200 Dafny specifications for MBPP-Dafny dataset
  - [*Towards AI-Assisted Synthesis of Verified Dafny Methods*. Misu, Lopes, Ma, Noble. FSE'24]
  - 50 hand-written, 153 GPT-4 generated and **manually** labeled {incorrect, weak, strong}
- Problem: Evaluate the soundness/completeness metrics
- Result
  - Translated the metrics into Dafny verification problems
    - Requires auxiliary assertions for arrays/sequences to help quantifier instantiation
  - Automated metrics gets parity with the human-labeling
  - Finds instances where a "strong" specification is not complete

```
"Write a function to find the shared elements
from the given two lists."

predicate InArray(a: array<int>, x: int)
  reads a
  {exists i :: 0 <= i < a.Length && a[i] == x}

method SharedElements(a: array<int>, b: array<int>) returns (result: seq<int>)
  ensures forall x :: x in result ==> (InArray(a, x) && InArray(b, x))
  ensures forall i, j :: 0 <= i < j < |result| ==> result[i] != result[j]

method SharedElementsTest(){
  var a1:= new int[] [3, 4, 5, 6];
  var a2:= new int[] [5, 7, 4, 10];
  var res1:=SharedElements(a1,a2);
                //expected[4, 5];
}
```

GPT4 generated. Labeled as “strong”

Our metric marks this as a weak specification (wrt the test)

Changing ==> to <==> makes it a strong invariant by our metric

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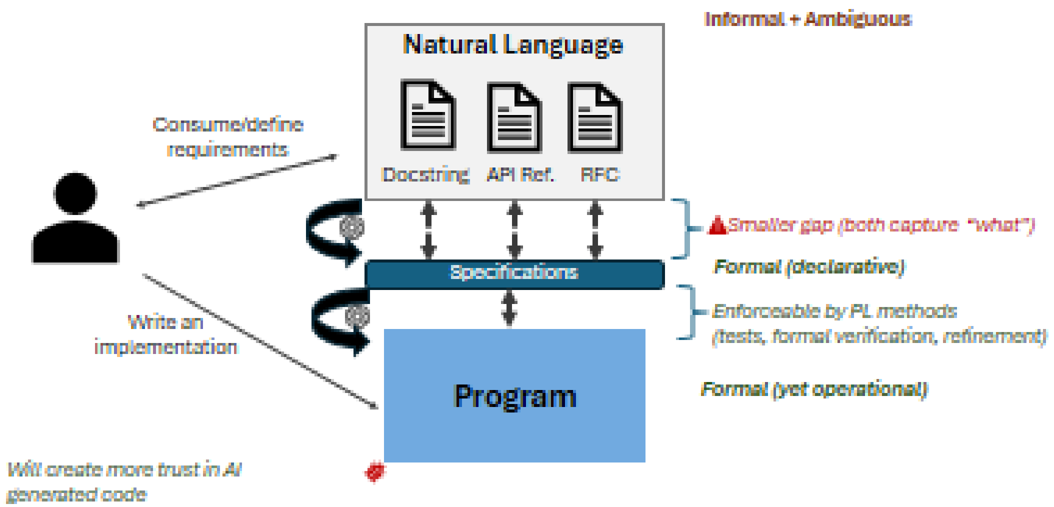

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Questions