Grammar-Based Fuzzing + Bug Explanations

Software Engineering II

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Agenda

Fuzzing 101
Automatic Input Generation

Grammar based Fuzzing
Advanced Input Generation

Automatic Debugging
Automatically Explaining the Circumstances of Program Faults

Martin Eberlein, Doctoral Researcher, SE 2 (2025)

Grammar-Based Fuzzing

Quality Assurance

Basic Fuzzing

Generating Program Input 101

- **Software Testing Technique**
  Many different flavors: Black-, Grey, and White-box fuzzer

- **Basic Fuzzer *randomly* generate Input**
  Most popular fuzzers: AFL (AFL++), libfuzzer, …

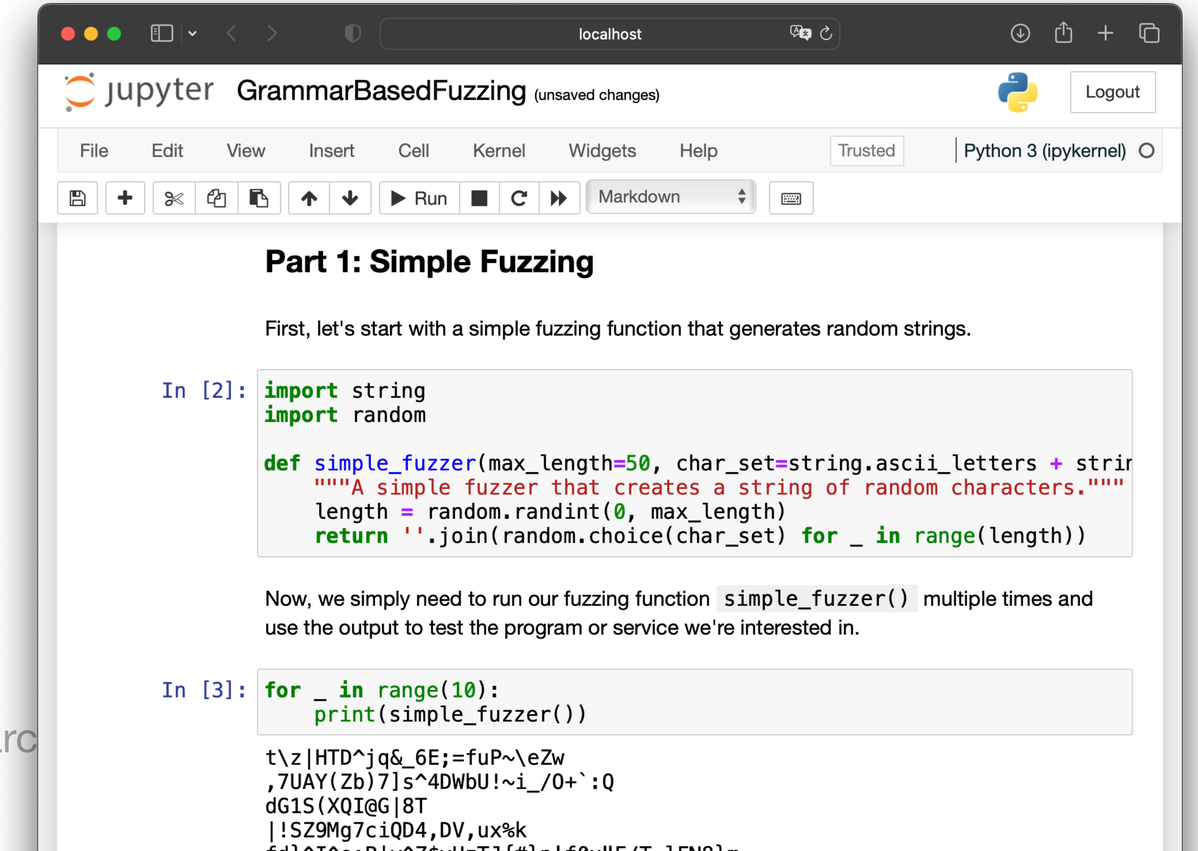
- **Fuzzing can be guided by properties**
  Most common strategies: code coverage, diverse inputs, …

- **Simple Fuzzers can easily be written by yourself!**
  Jupyter-Notebook

Basic Fuzzing

Generating Program Input 101

- **Simple Fuzzers can easily be written by yourself!**
  Jupyter-Notebook



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Grammar-Based Fuzzing

Like *Fuzzing* with extra steps

- Most applications require structured input

Web applications, interpreters, and parser require syntactically valid input

- Guided by Grammars

Input generation can be guided by context free grammars to produce syntactically valid inputs

- More Efficient! 

Input generation can be guided by context free grammars to produce syntactically valid inputs

Grammar-Based Fuzzing

Like *Fuzzing* with extra steps

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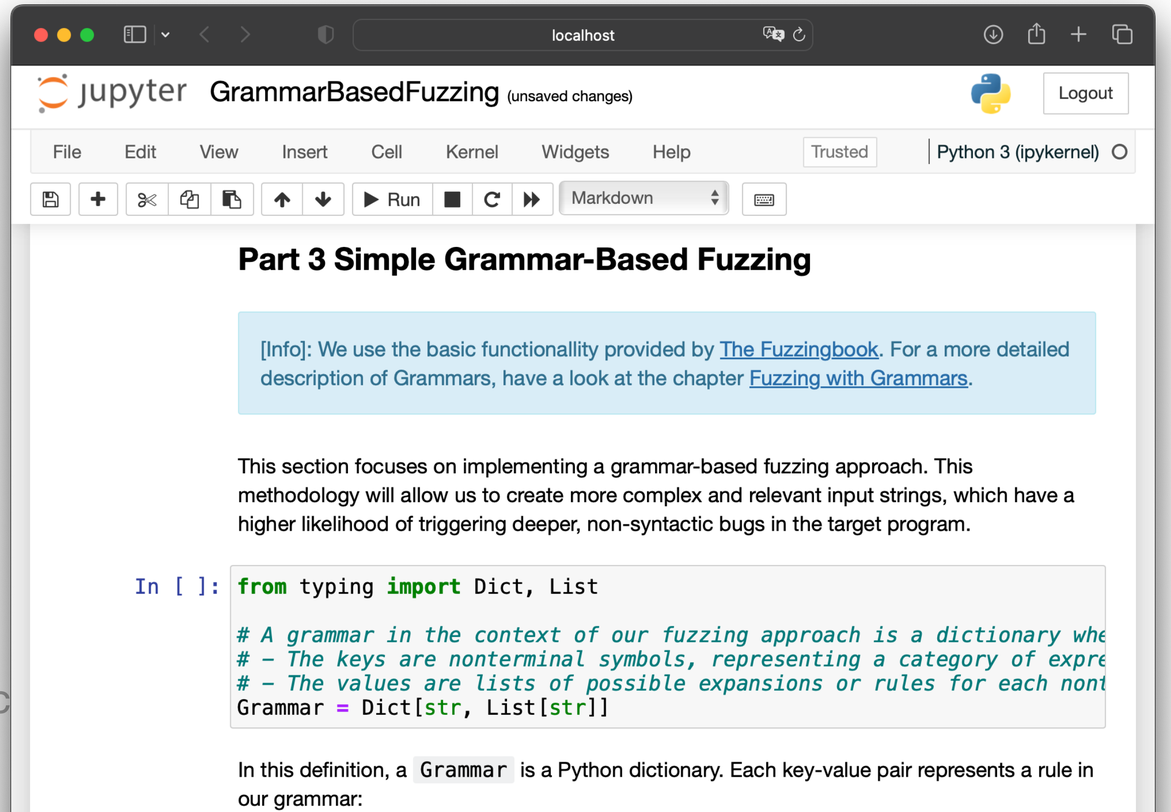

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Probabilistic Grammar-Based Fuzzing

Guided by Probabilities

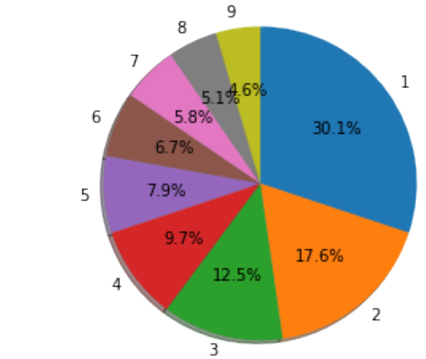
- **More Efficient!**

  Input generation can be guided by context free grammars to produce syntactically valid inputs

- **Observation:**

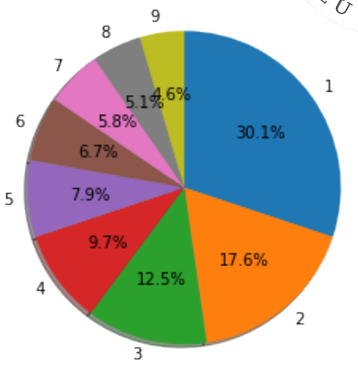
  Some Features are more important than others

- **Example: Law of the Leading Digits**
  - In real-world data sets of numerical data, the leading digit is likely to by small
  - [Newcomb 1881, Benford 1938]



Probabilistic Grammar-Based Fuzzing

Guided by Probabilities



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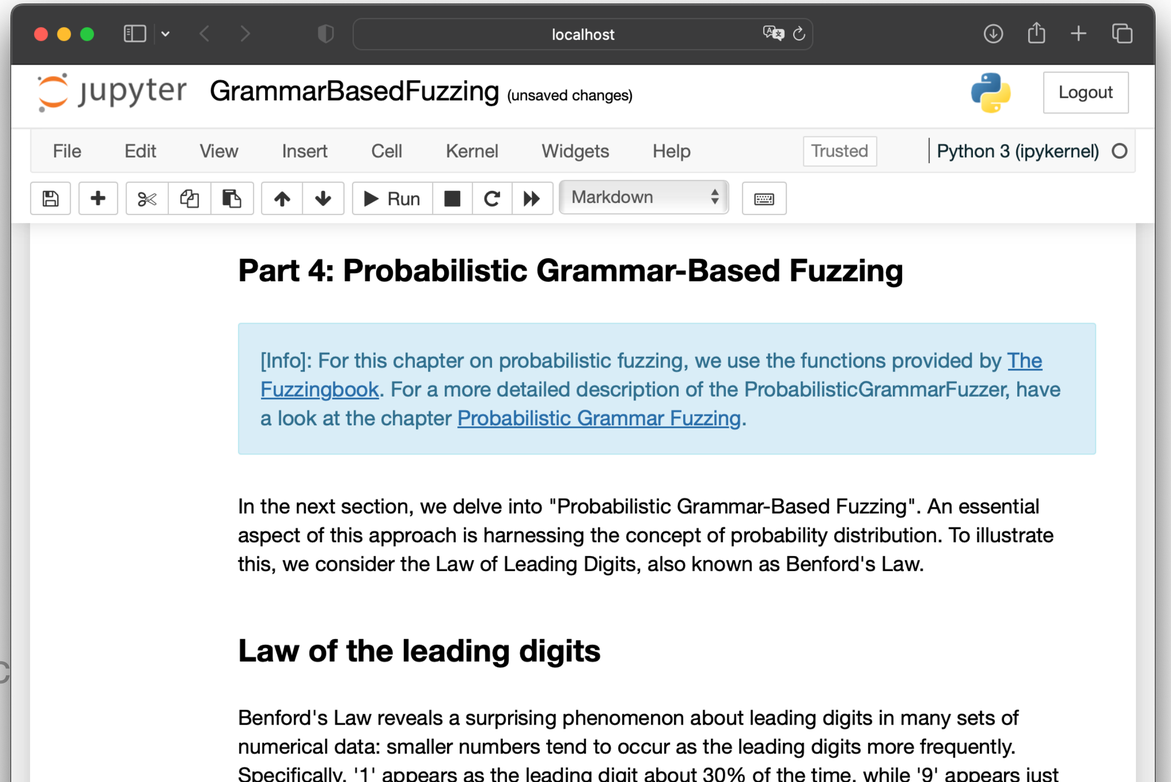

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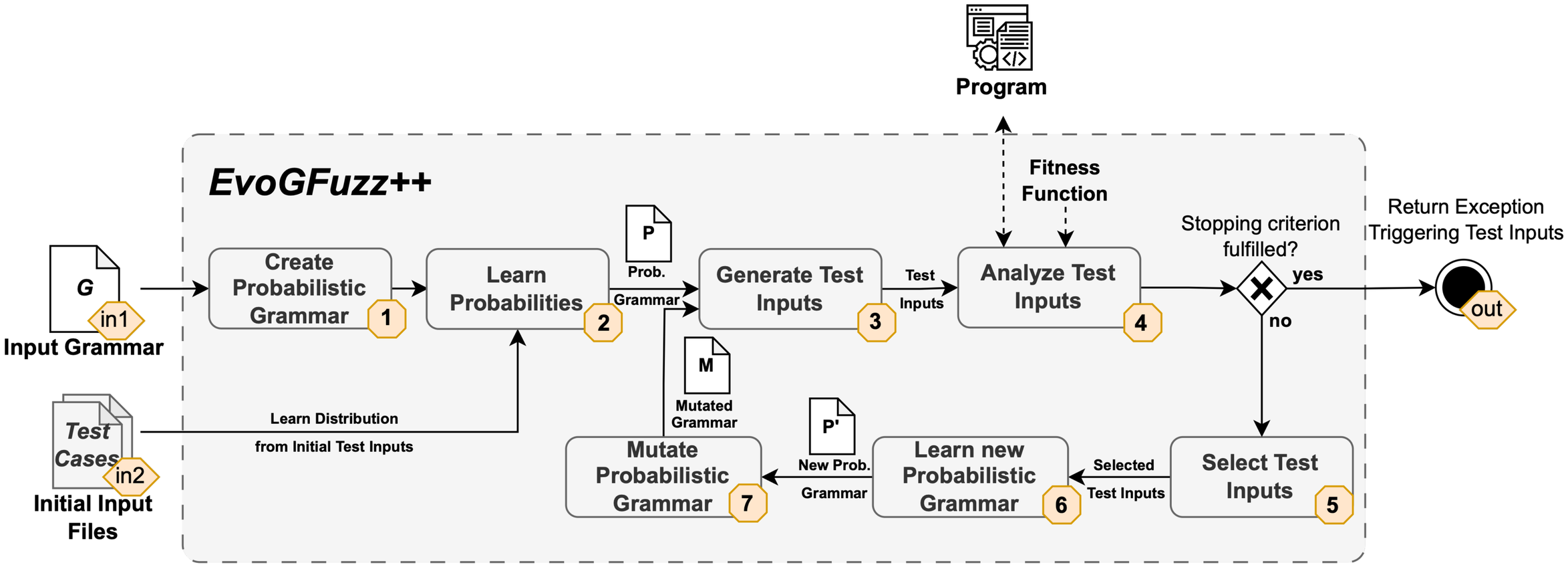
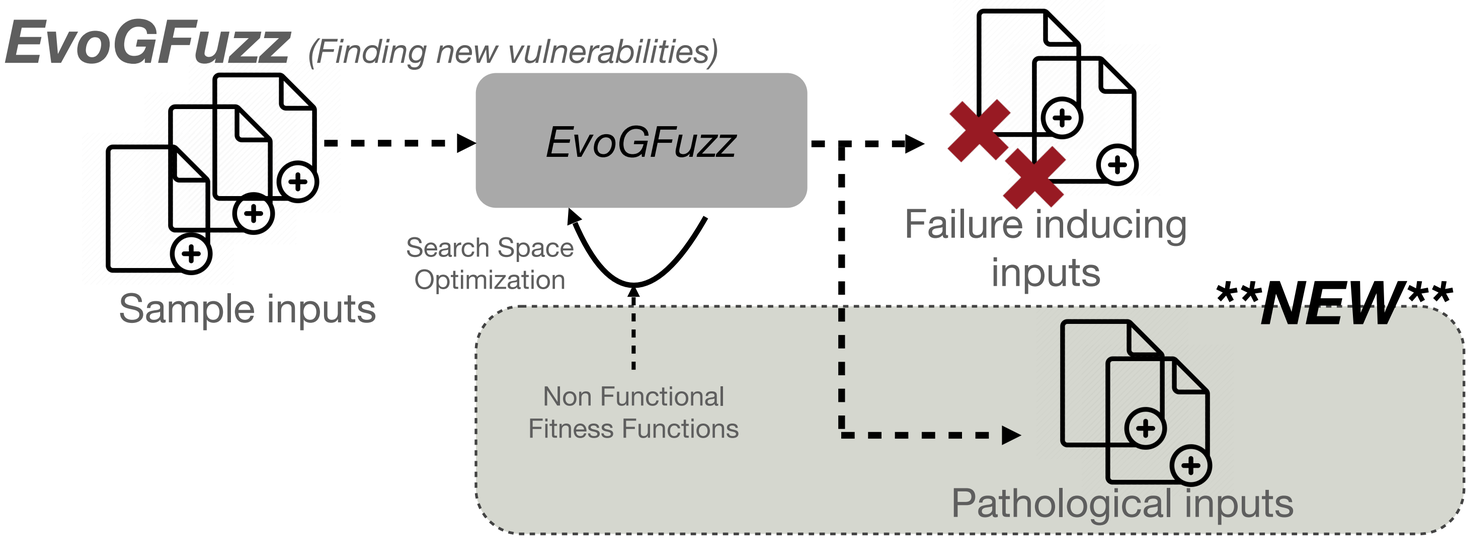
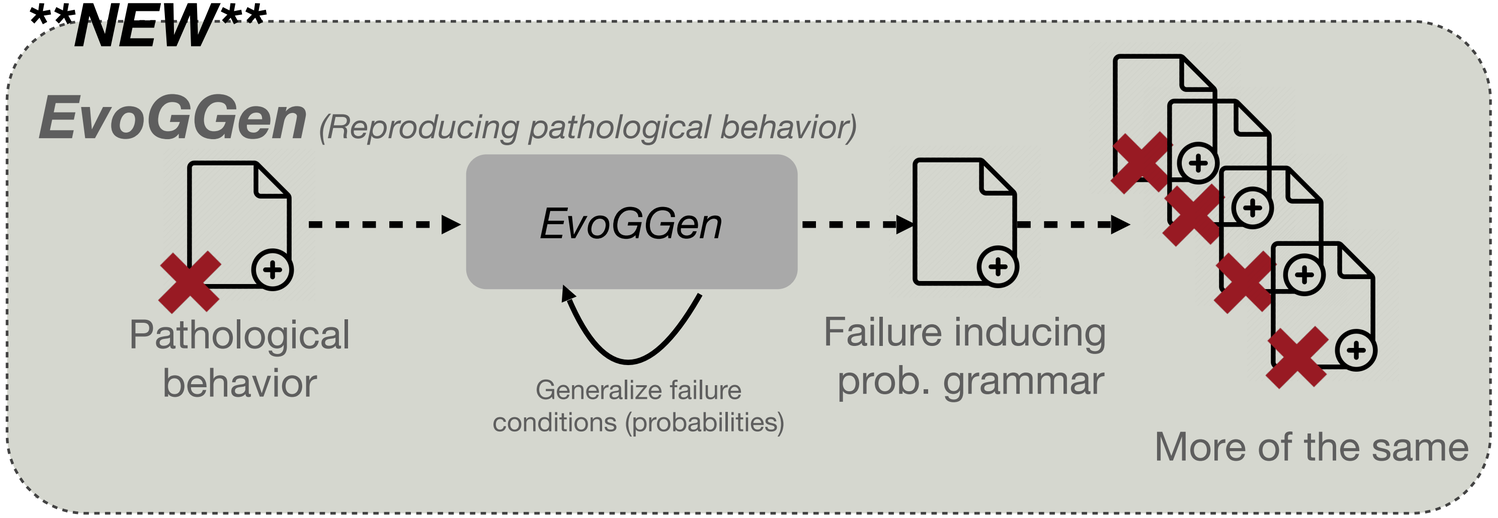
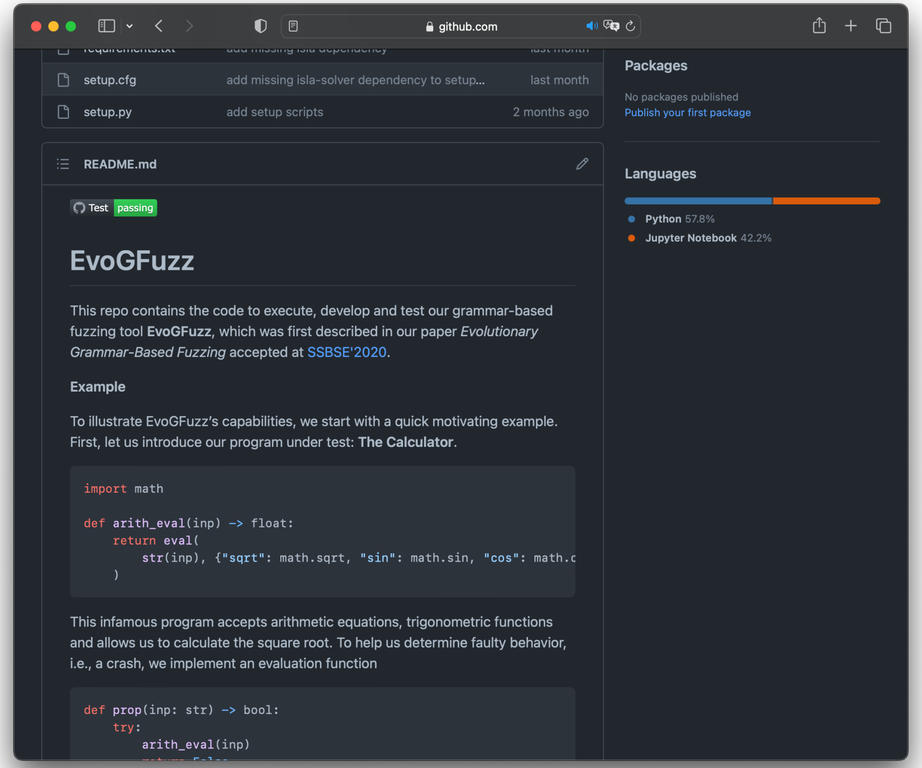
Evolutionary Grammar-Based Fuzzing



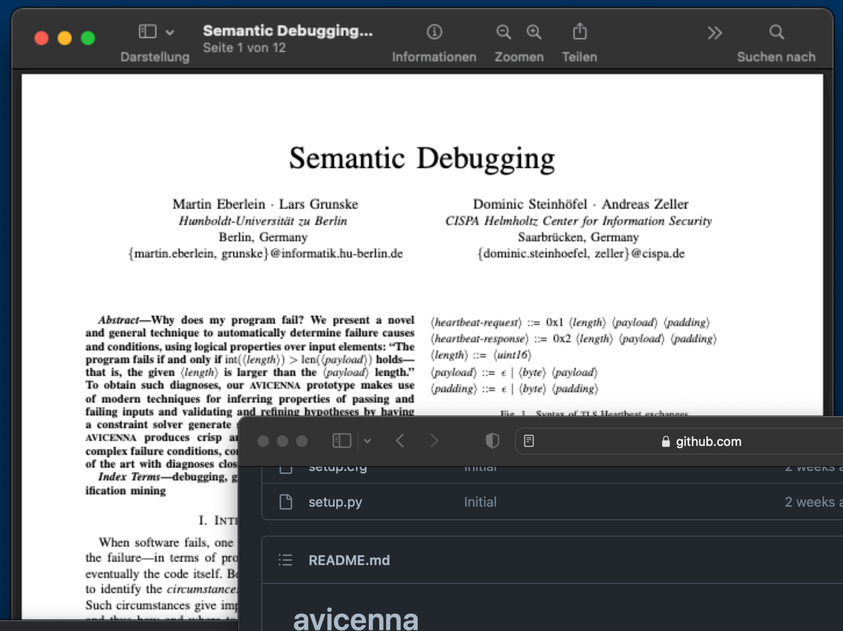
Evolutionary Grammar-Based Fuzzing

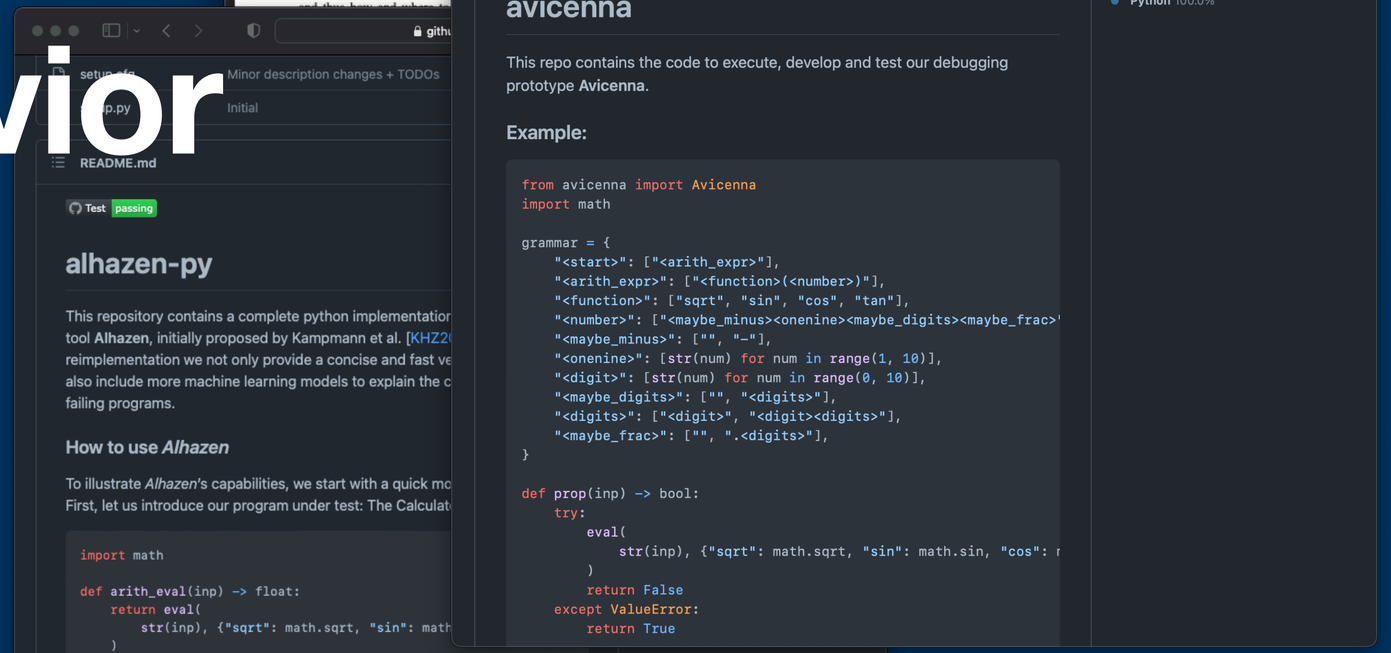




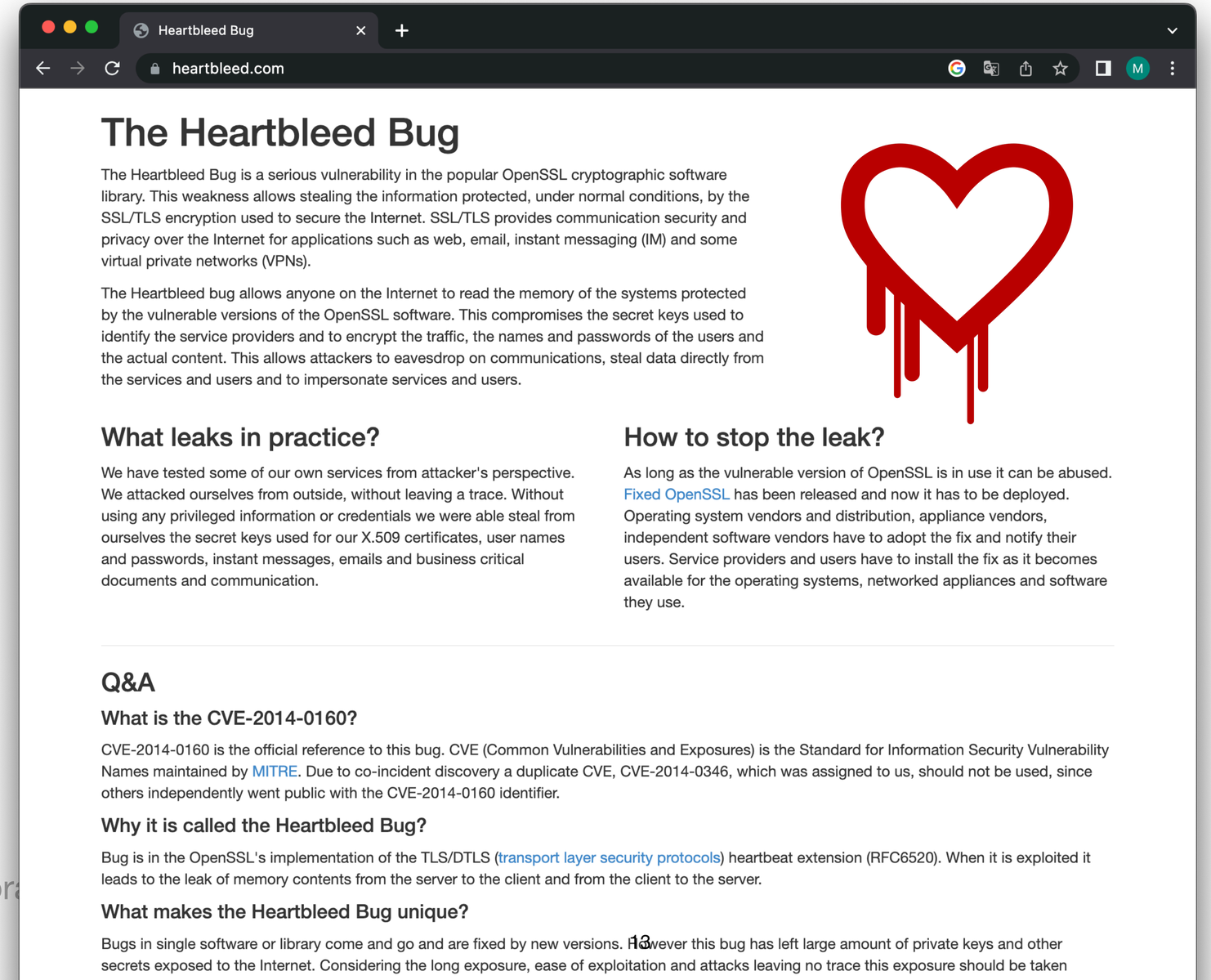


Explaining Pathological Program Behavior





Heartbeat Protocol



Heartbeat Protocol

Client

Server

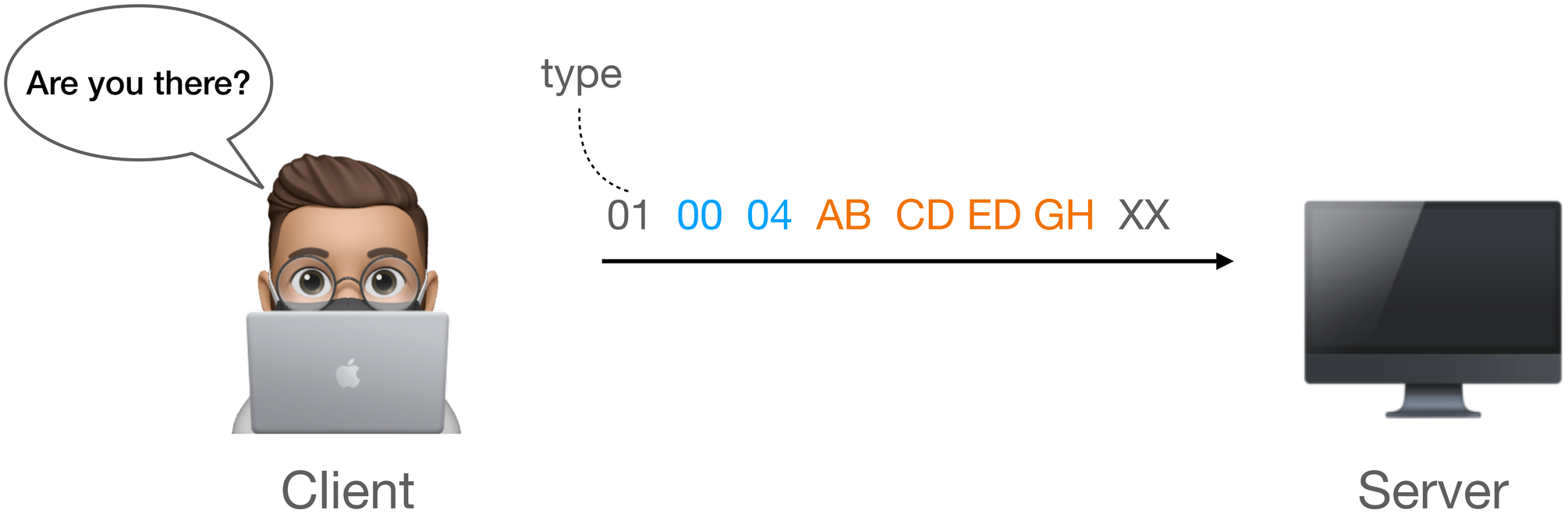
Heartbeat Protocol

Client

01 00 04 AB CD ED GH XX

Server

Heartbeat Protocol



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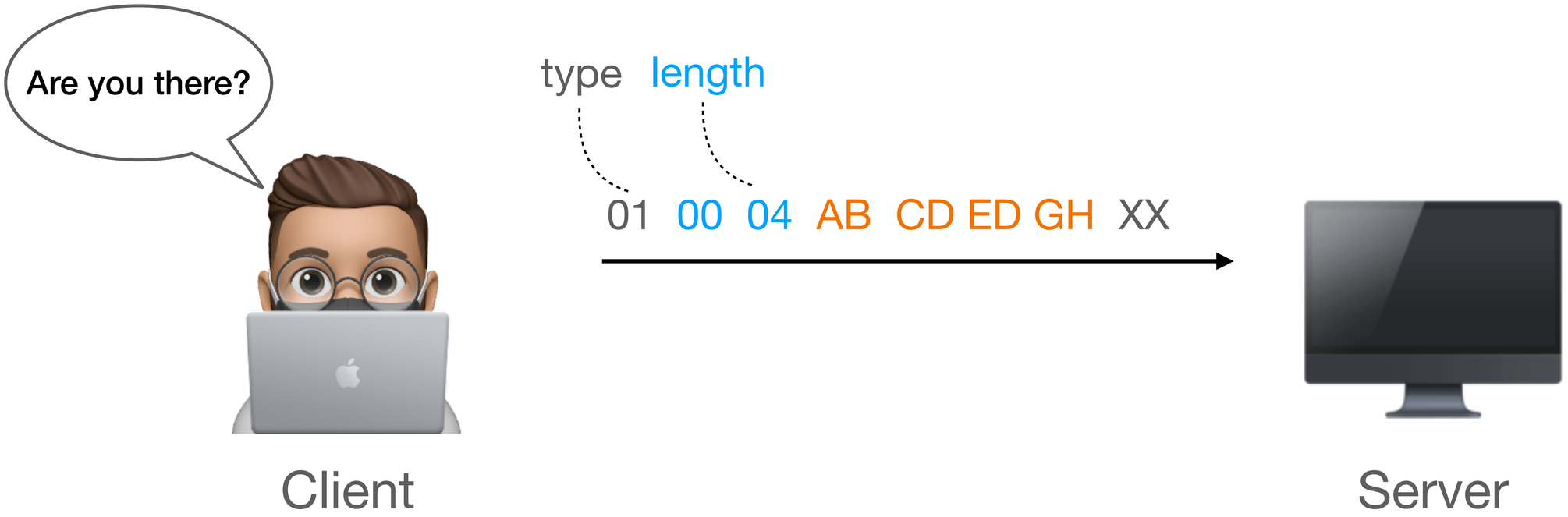

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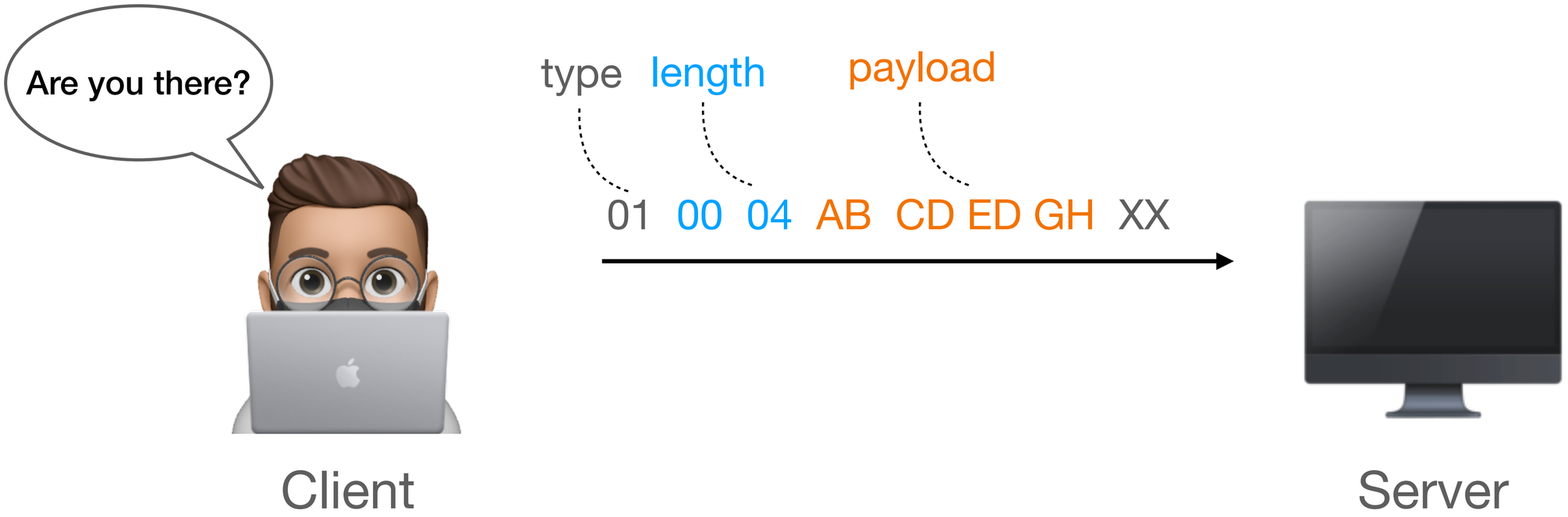


Heartbeat Protocol

Client

type length payload padding

01 00 04 AB CD ED GH XX

Server

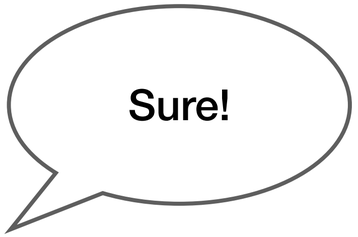
Heartbeat Protocol

Client

type length payload padding

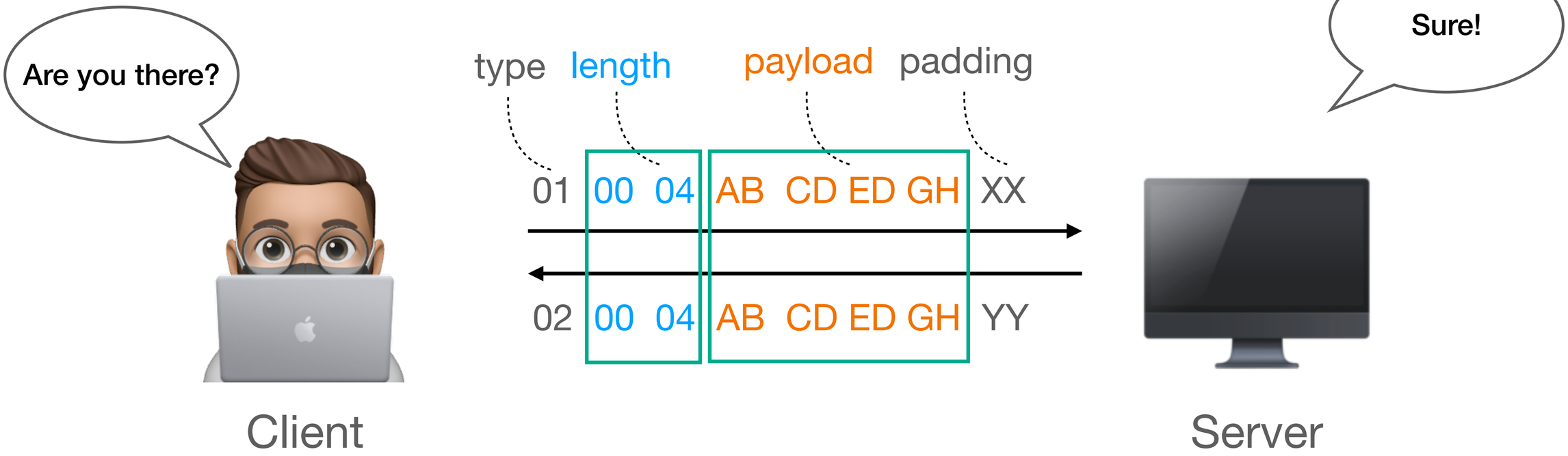
01 00 04 AB CD ED GH XX

02 00 04 AB CD ED GH YY



Server

Heartbeat Protocol



Heartbeat Protocol

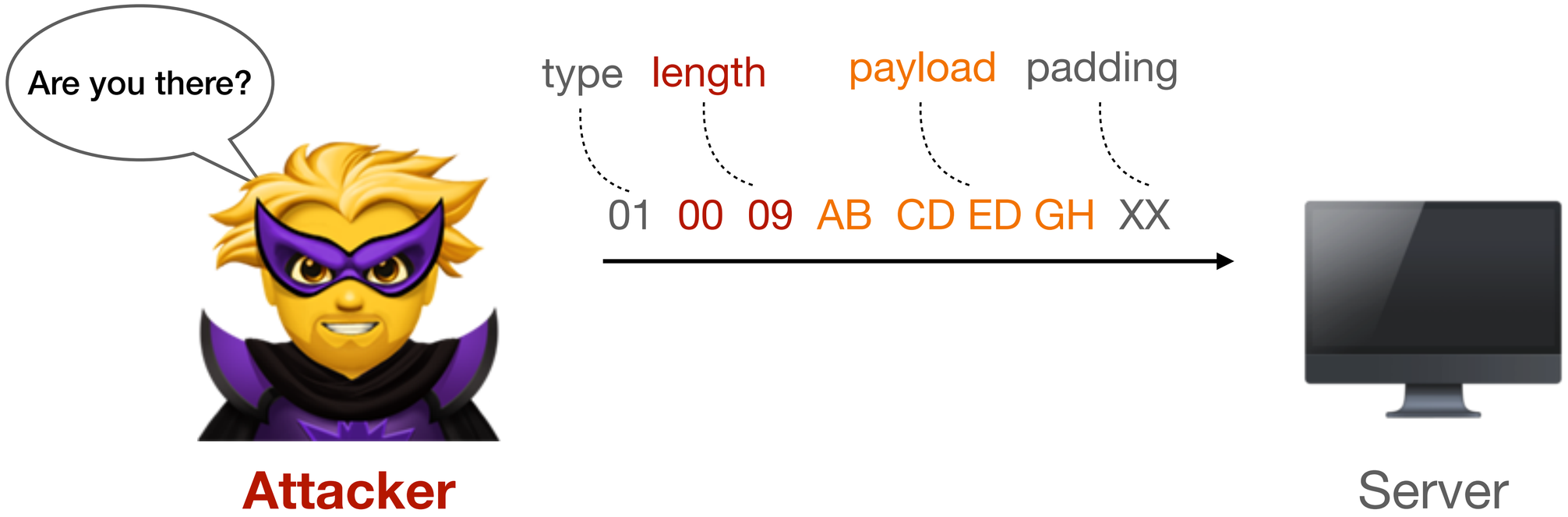
Exploit

Attacker

Server

Heartbeat Protocol

Exploit



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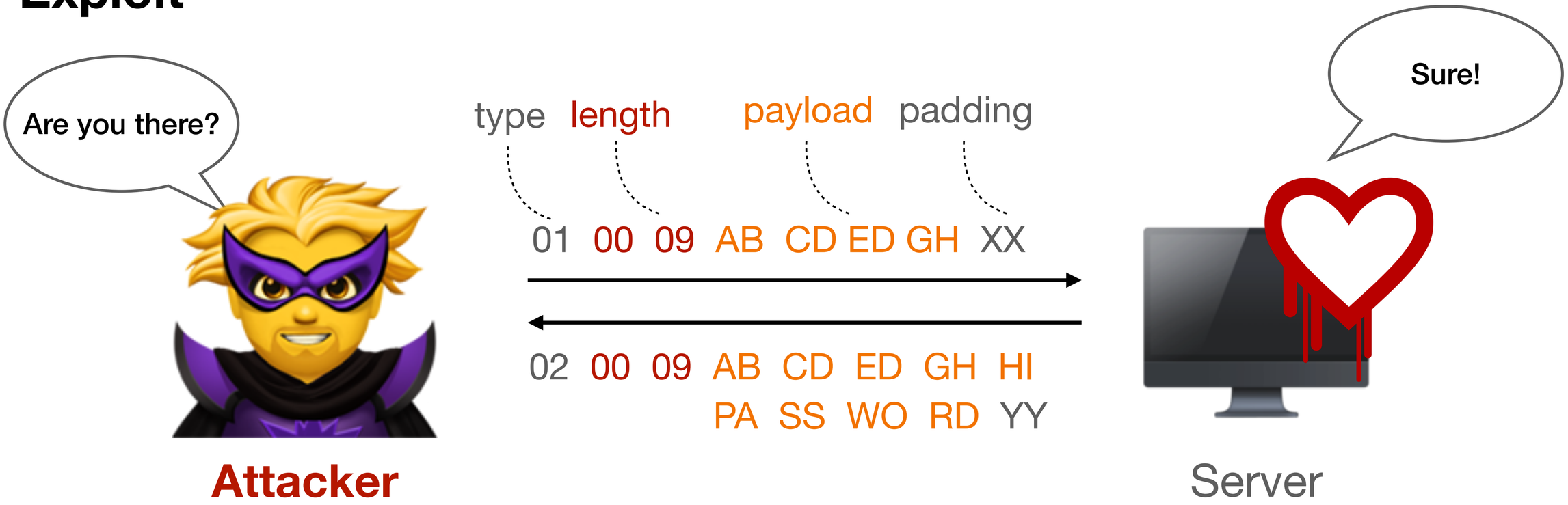

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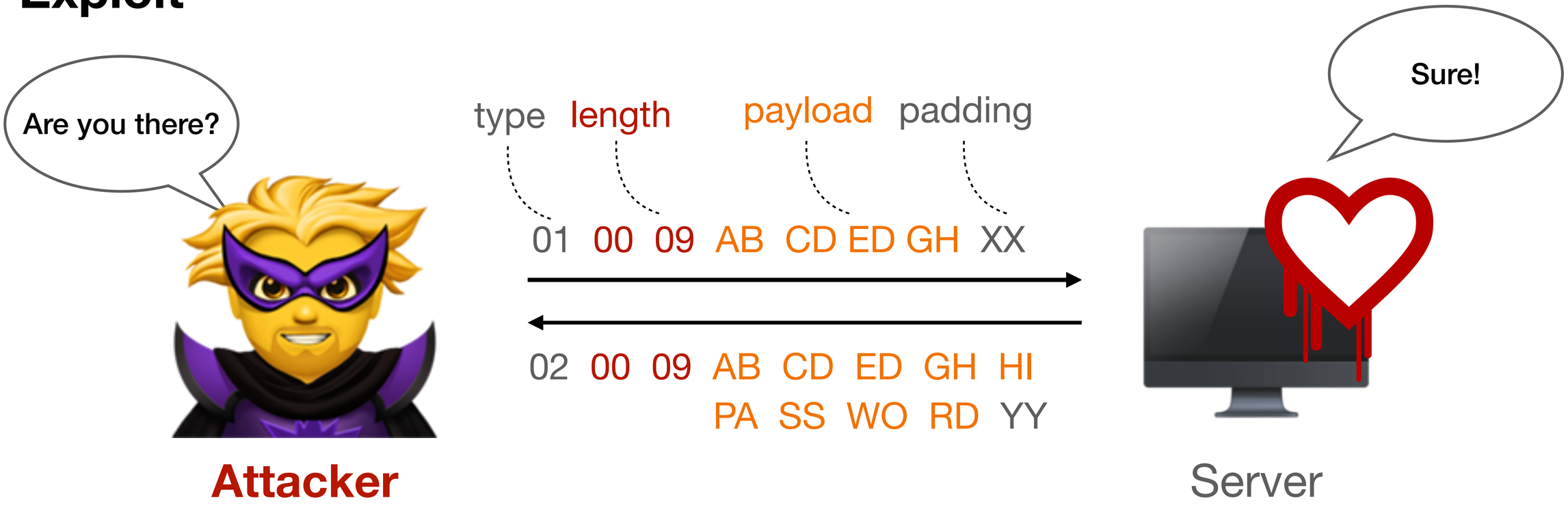
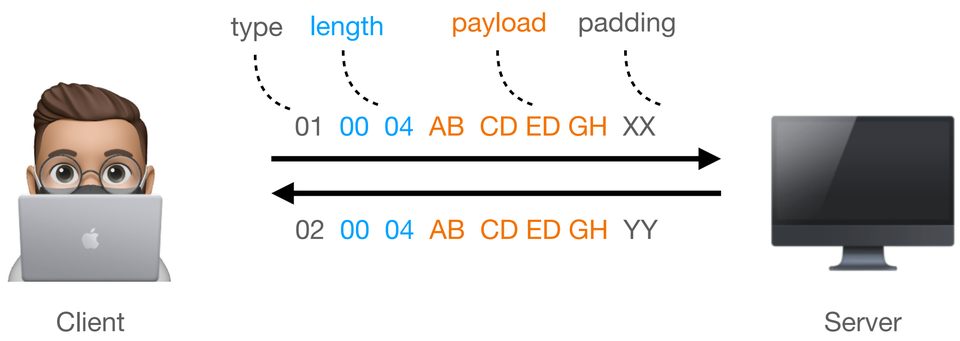
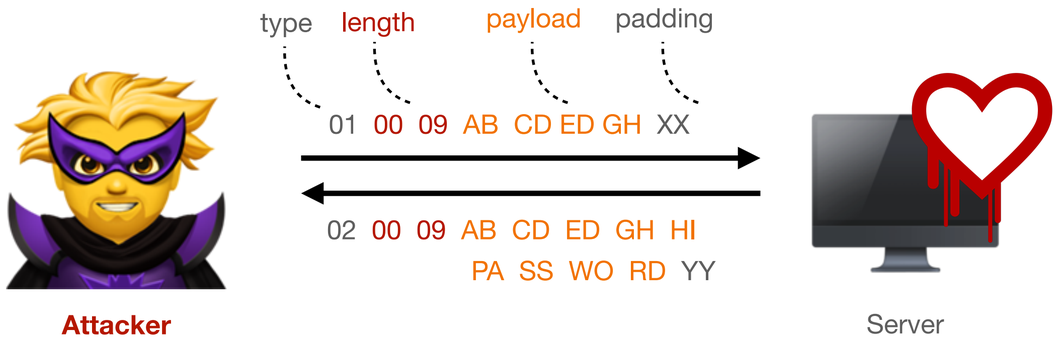


The *heartbleed bug* occurs if
int(*length*) > ***length***(*payload*)

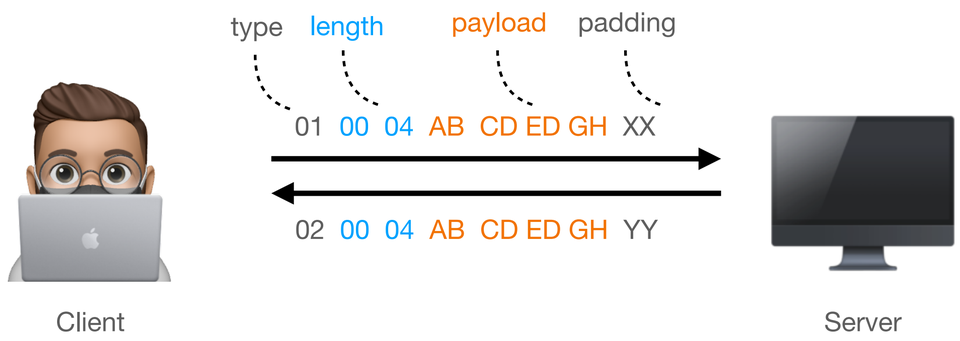
Explaining Program Behavior

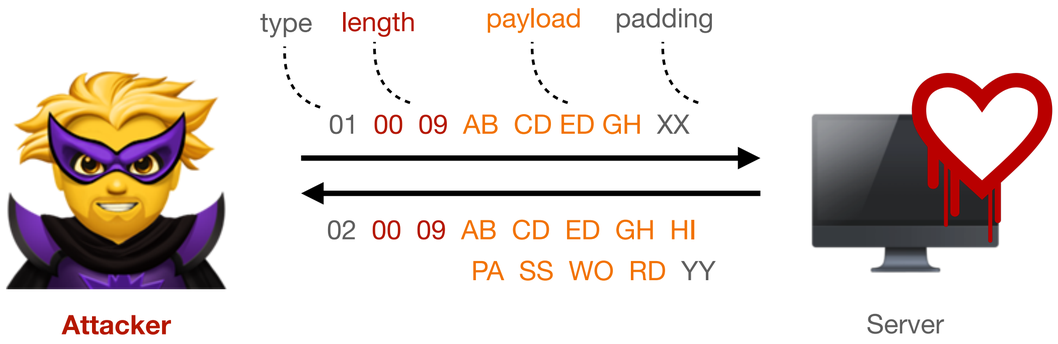




Can we **automatically** generate a **theory** explaining why a given input triggers the bug?

Explaining Program Behavior





Can we **automatically** generate a **theory** explaining why a given input triggers the bug?

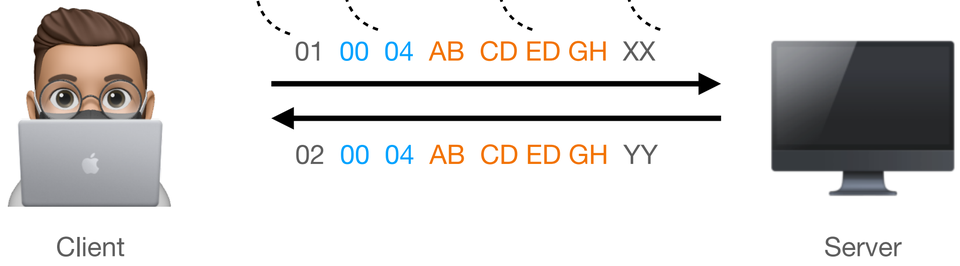
Possible Theories:

```
payload >= 9

length > 7

length > payload
```

Explaining Program Behavior



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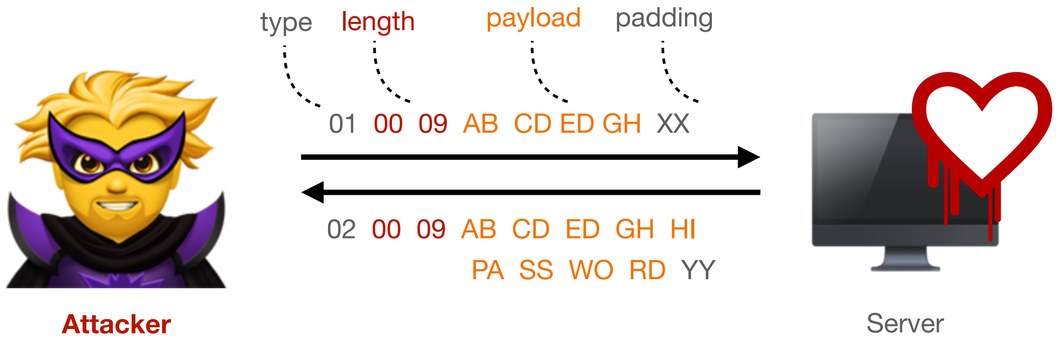
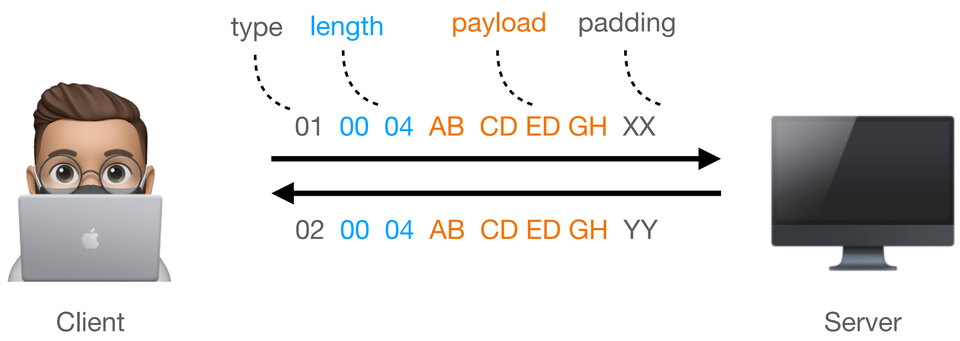


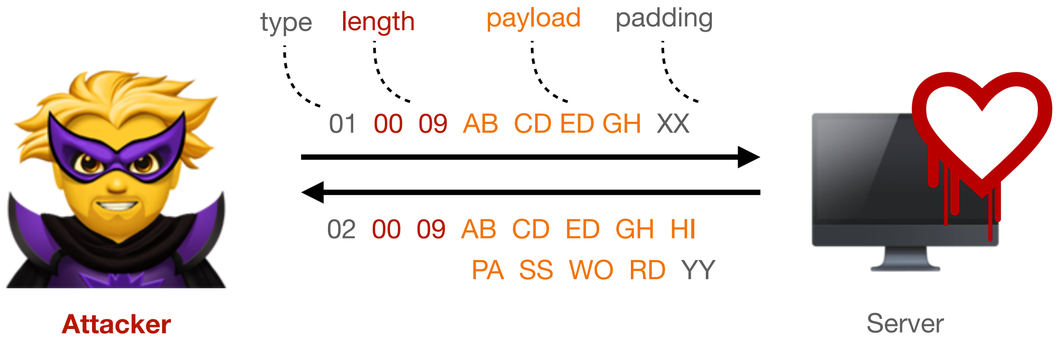
Observe Interactions

Input Generator

```
⟨request⟩::=
   0x1 ⟨length⟩⟨payload⟩⟨padding⟩
```

Explaining Program Behavior





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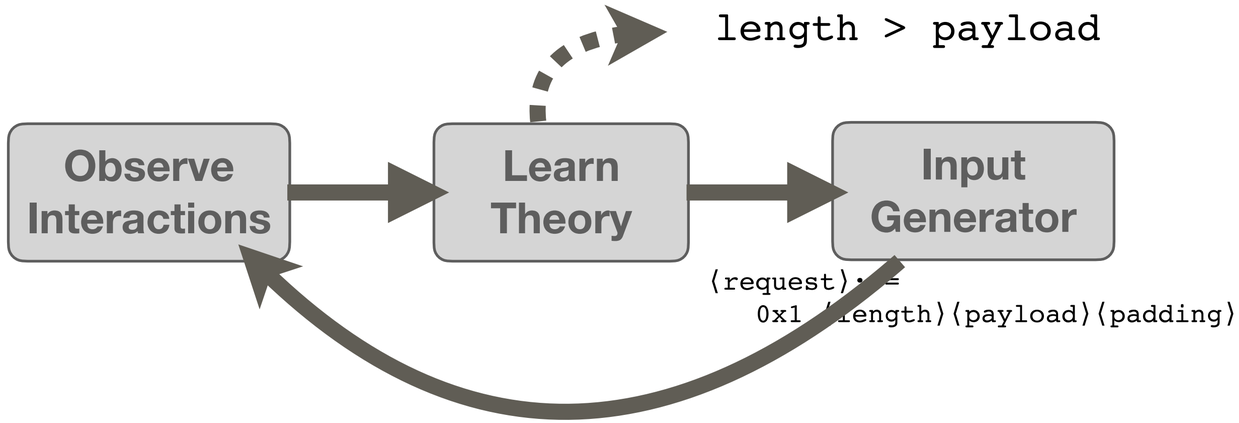
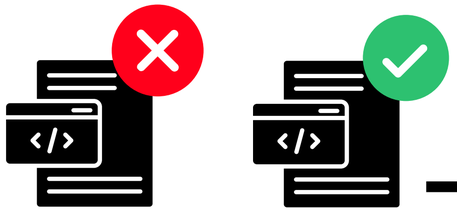


Semantic Debugging

Learning Failure Circumstances



test inputs

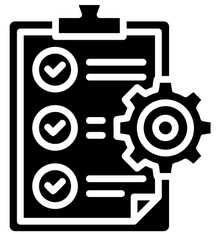
passing + failing

```
⟨request⟩::= 0x1 0x2000 „hello“
             0x0 …
```

Input specification

```
⟨request⟩::=
   0x1 ⟨length⟩⟨payload⟩⟨padding⟩
```

AVICENNA

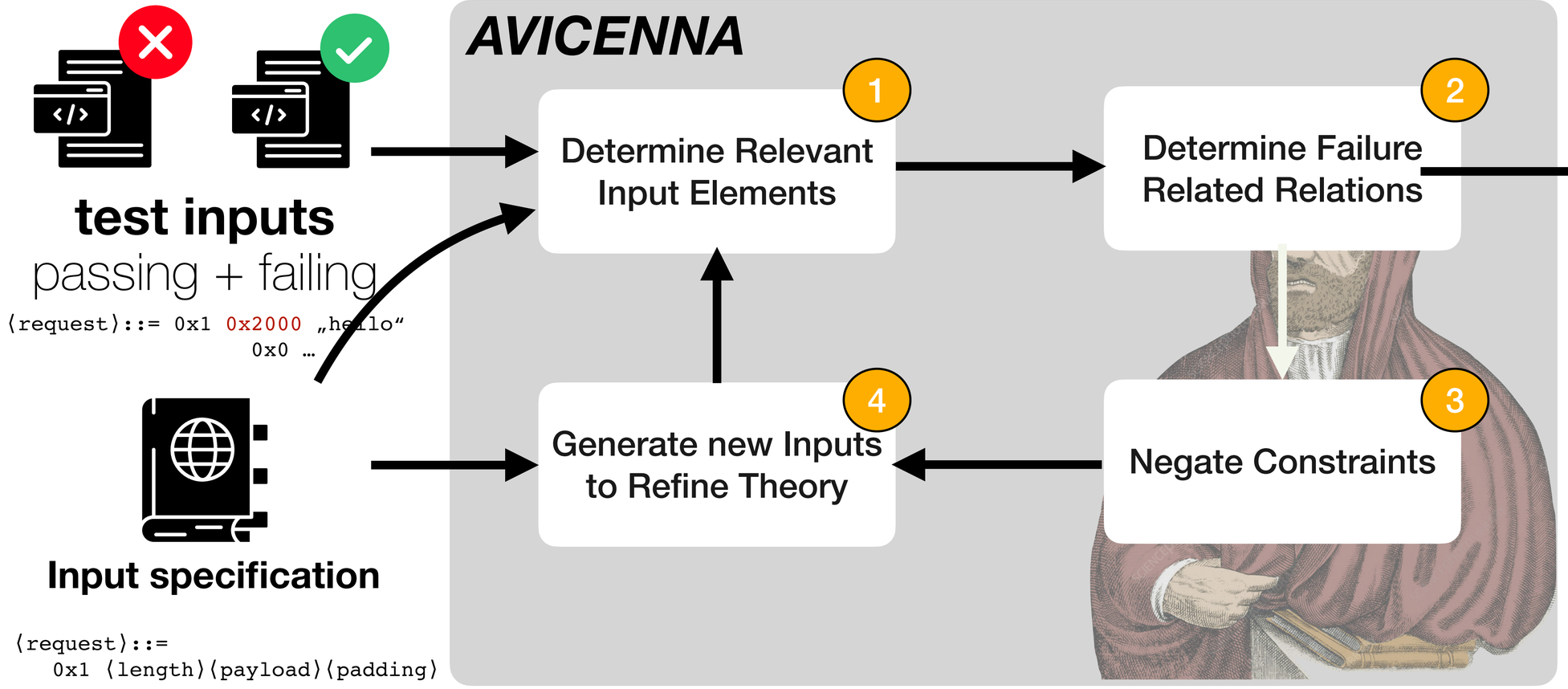


Failure Circumstances

```
int(⟨length⟩)
   > len(⟨payload⟩)
```

Semantic Debugging

Learning Failure Circumstances



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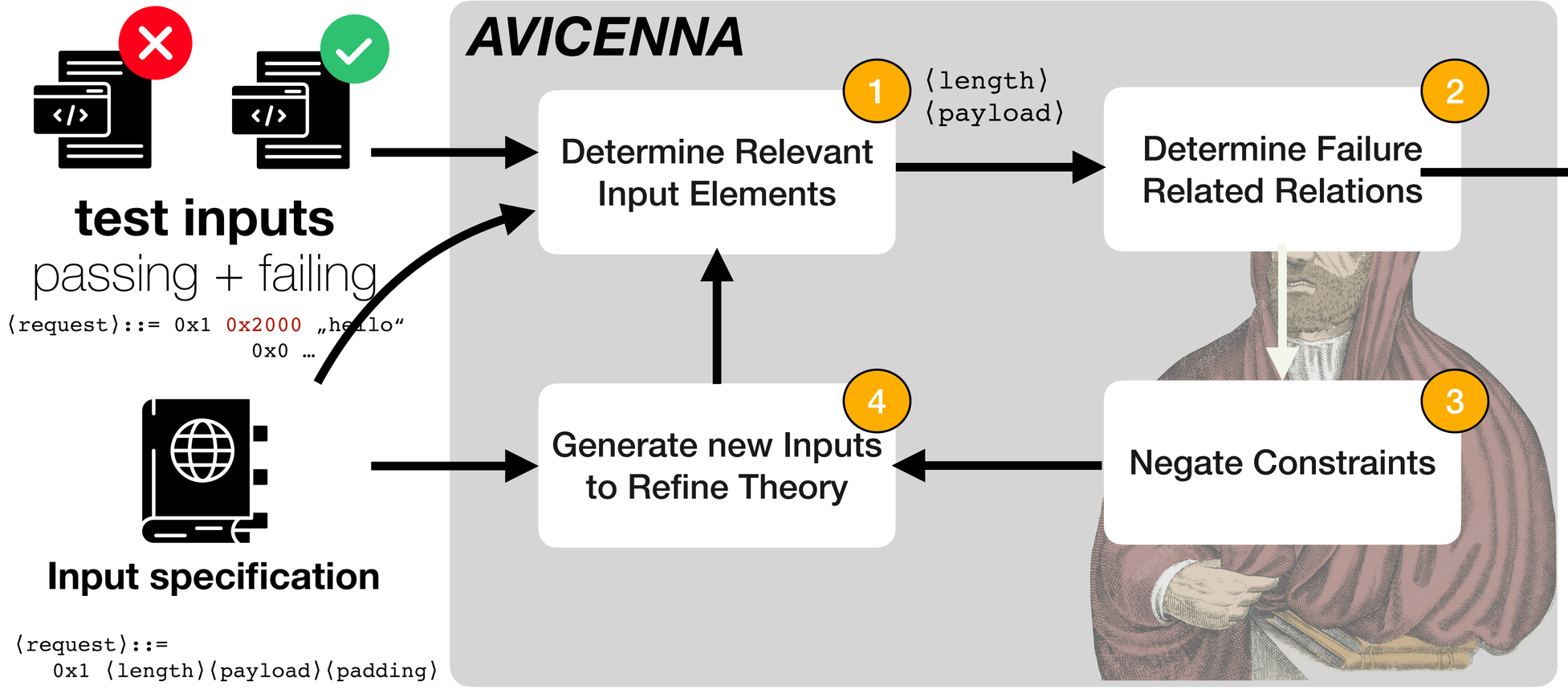

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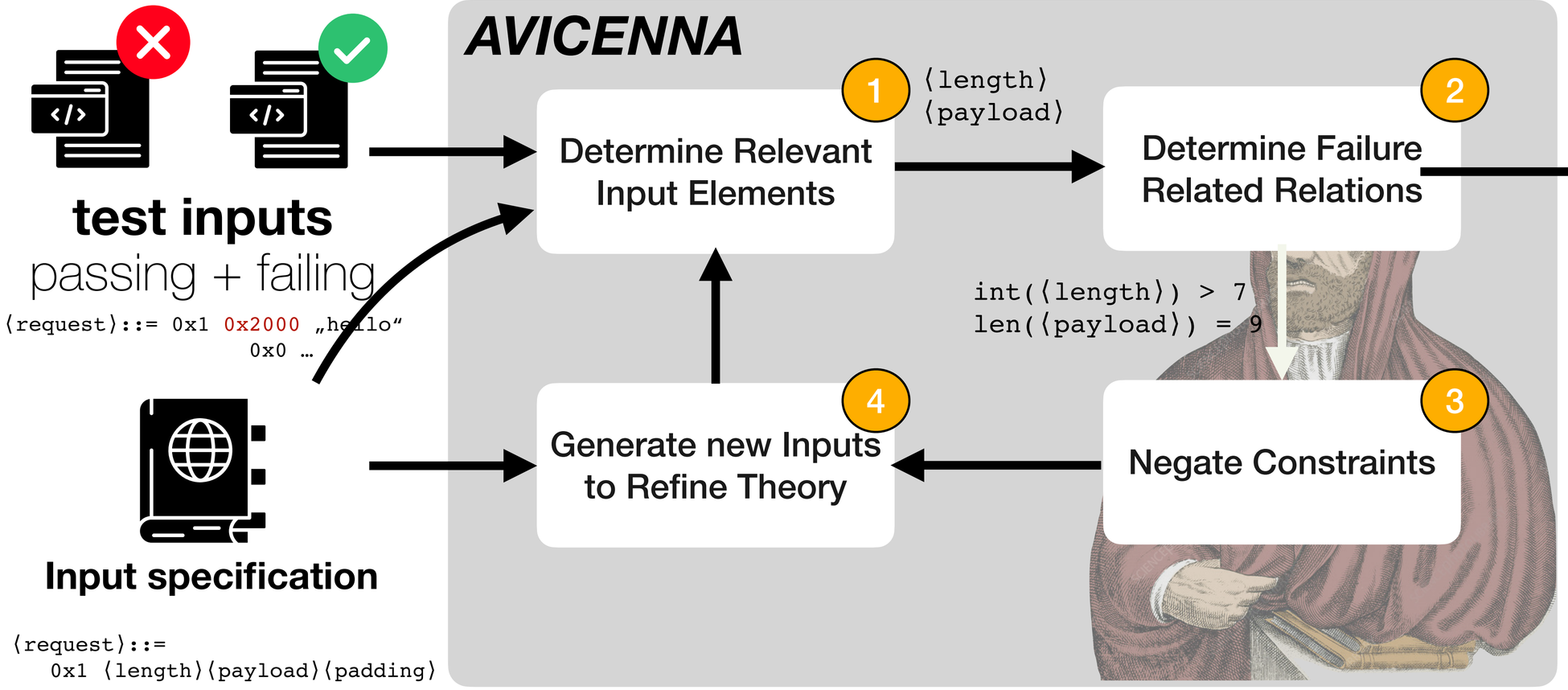

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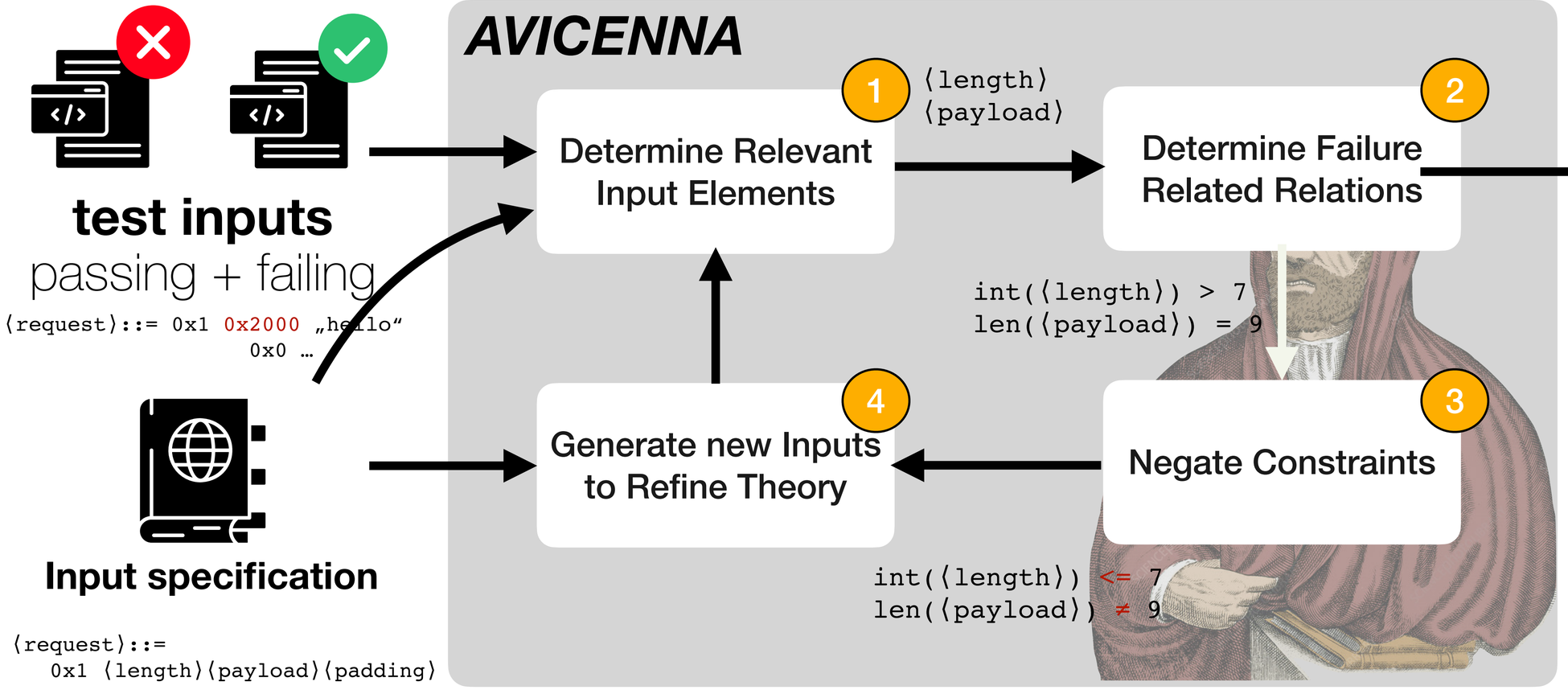

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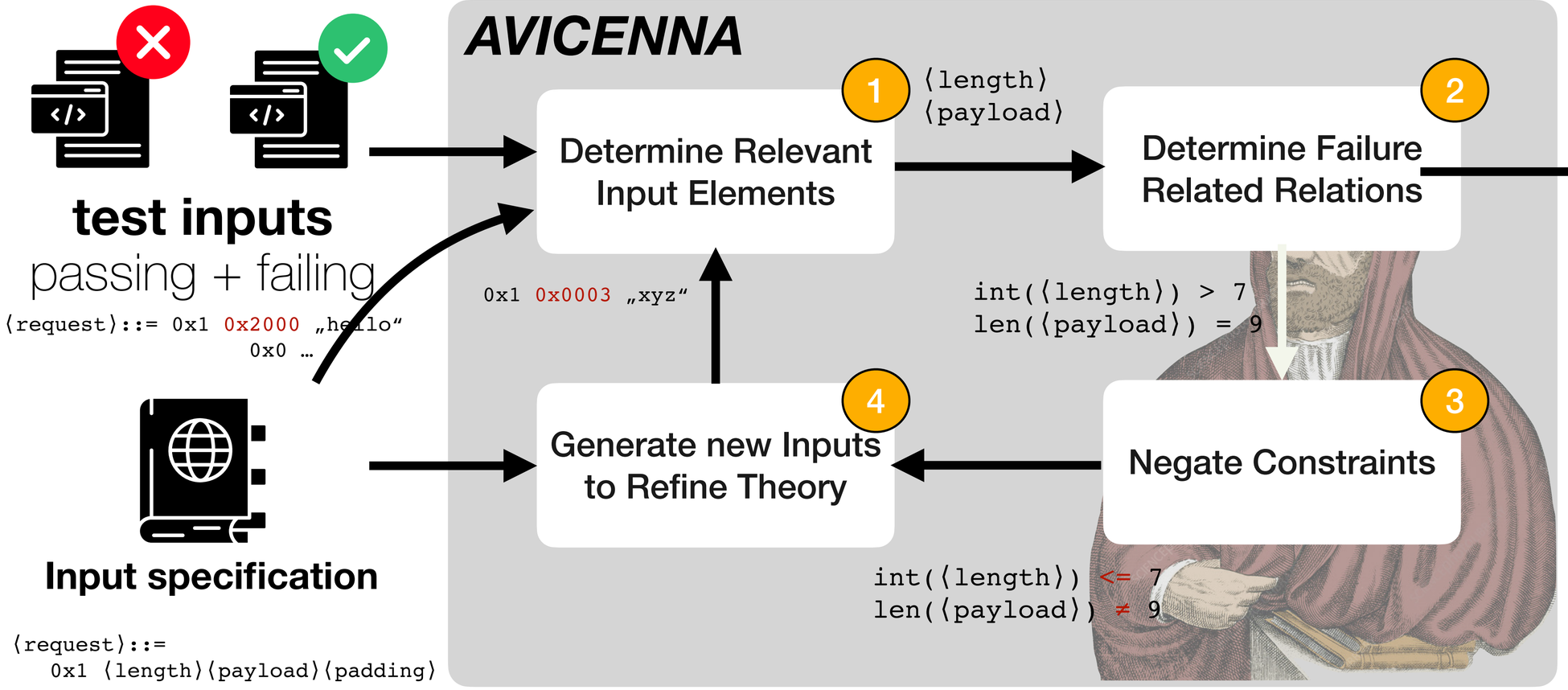

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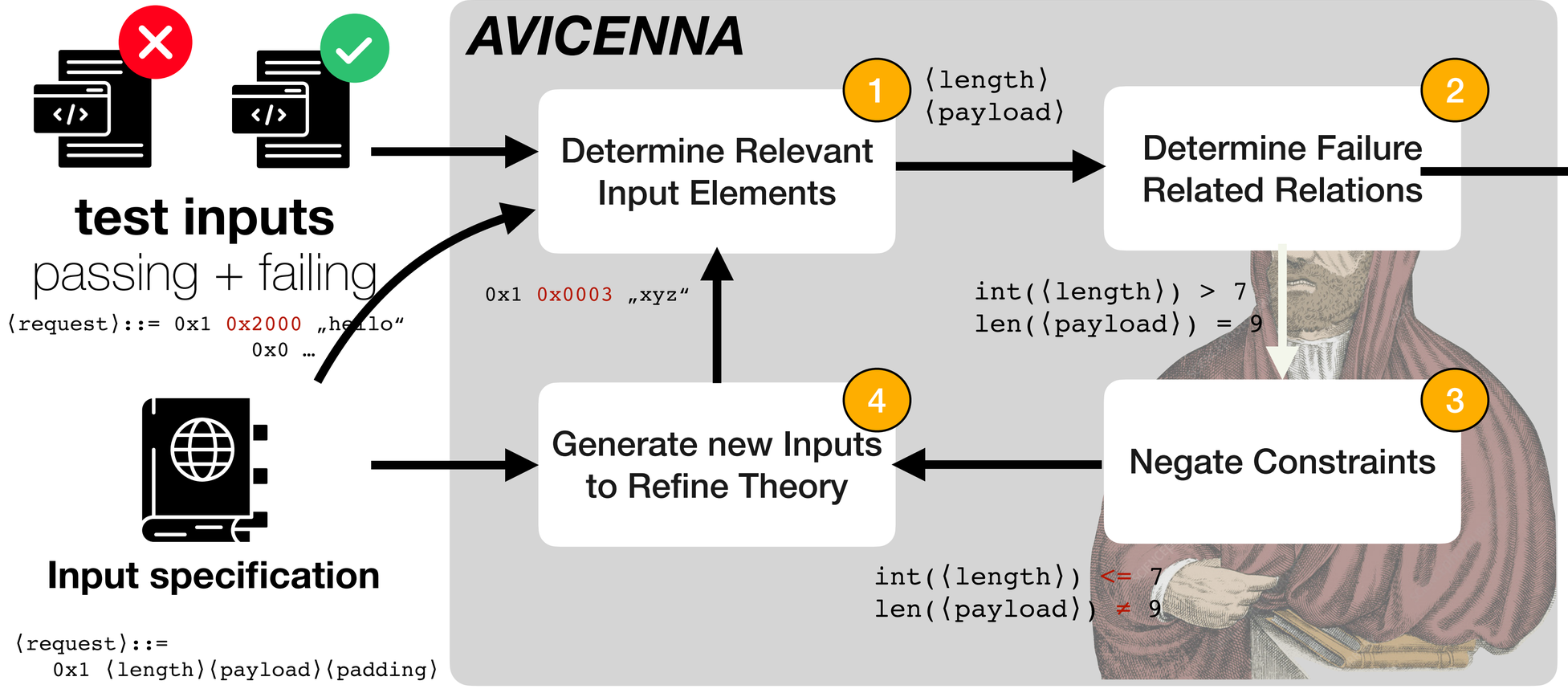
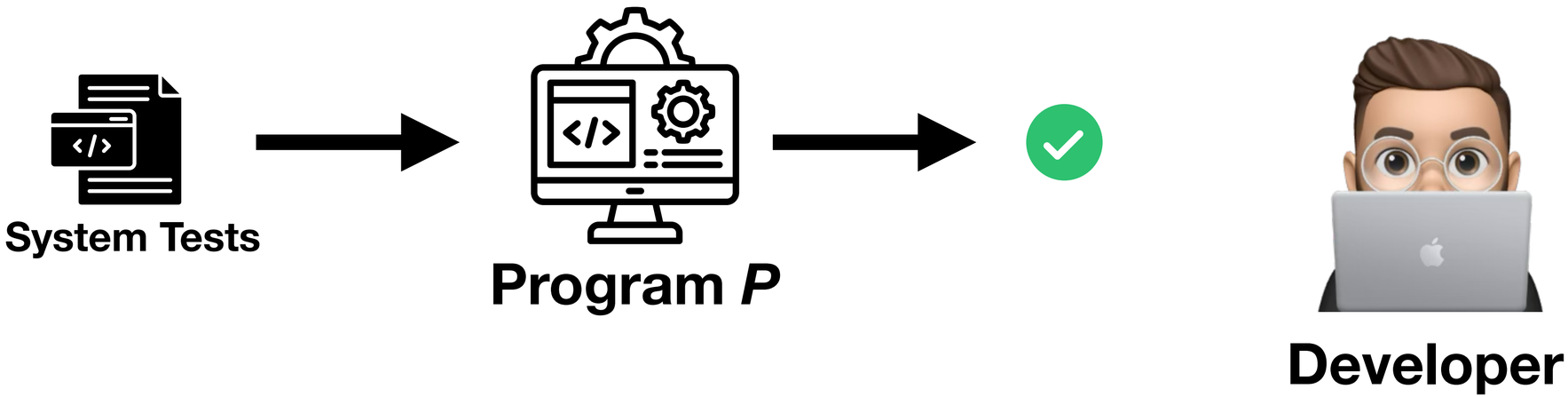


Which Inputs Trigger my Patch?

Generating explanations to describe the input properties affected by a patch

Trust Issues?

Would you trust a patch generated by ChatGPT to fix your critical code?



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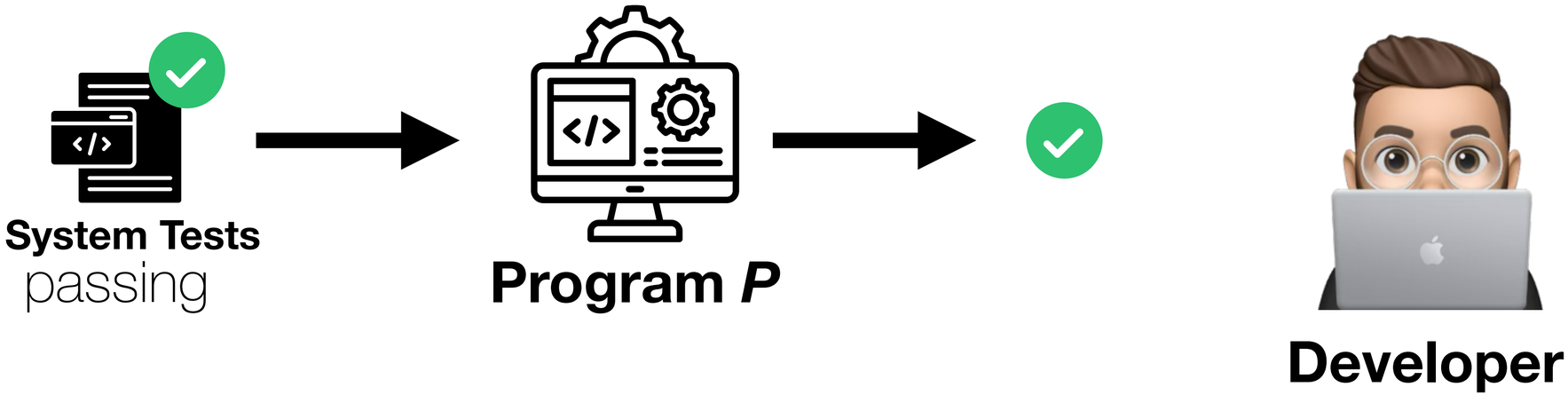

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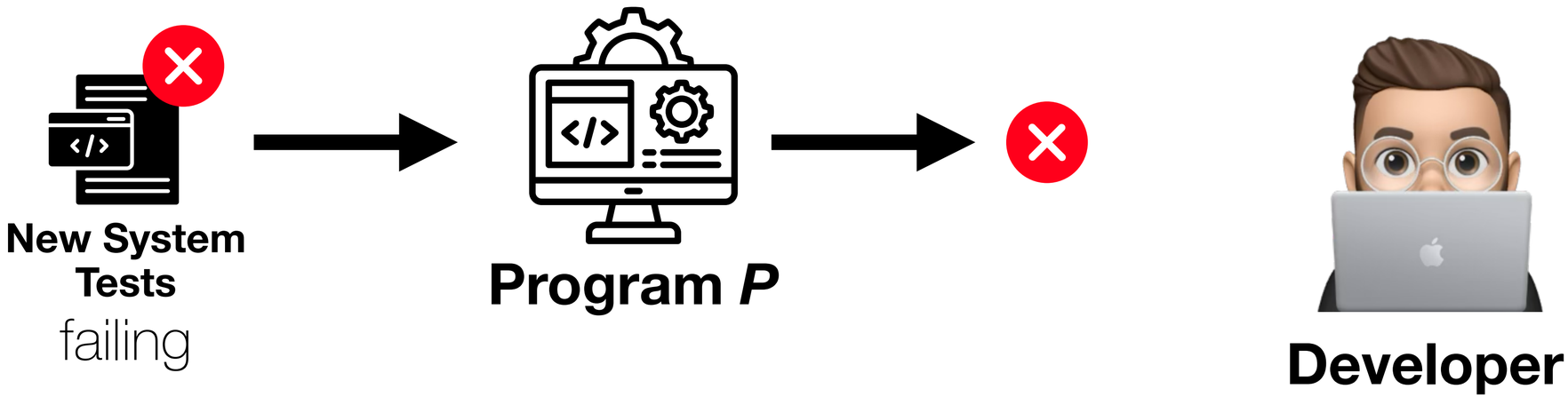

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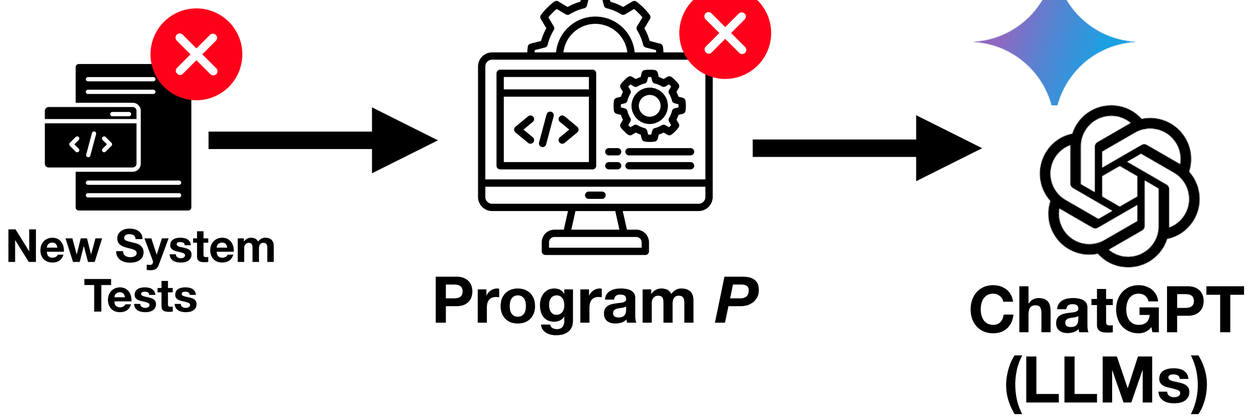

Developer

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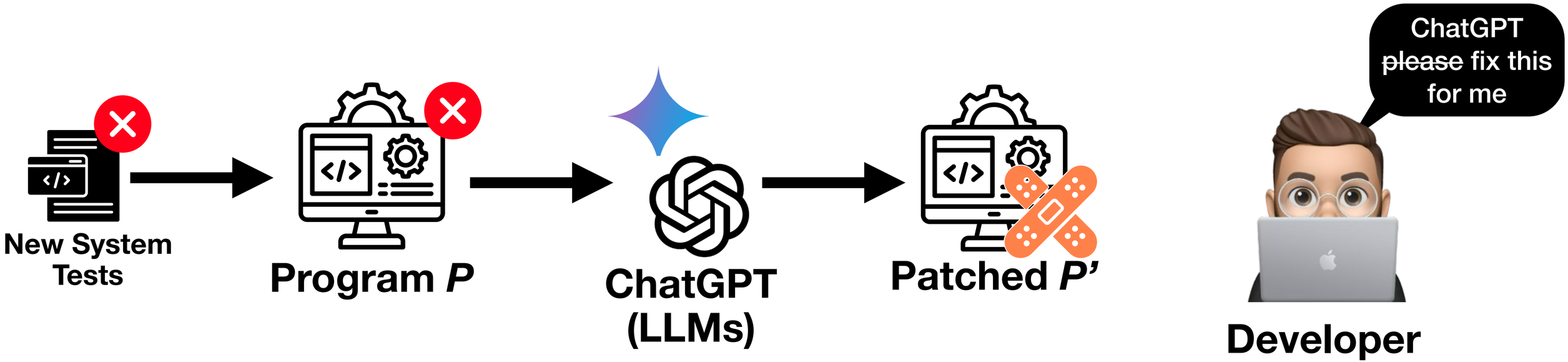

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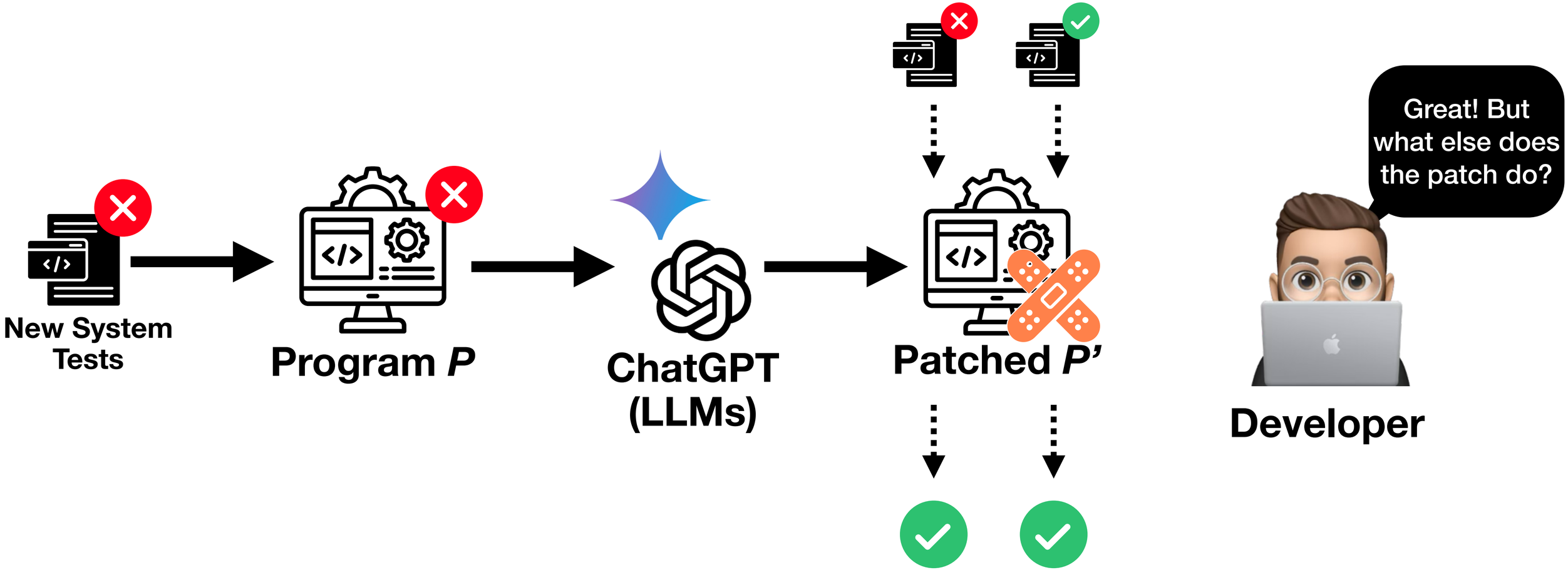


Trust Issues?

The Core Issue

- APR tools—including those powered by LLMs—are powerful but often opaque.
- It's unclear exactly which inputs are affected by these automatically generated patches.
- This lack of clarity creates significant trust issues for developers.

Developer

Trust Issues?

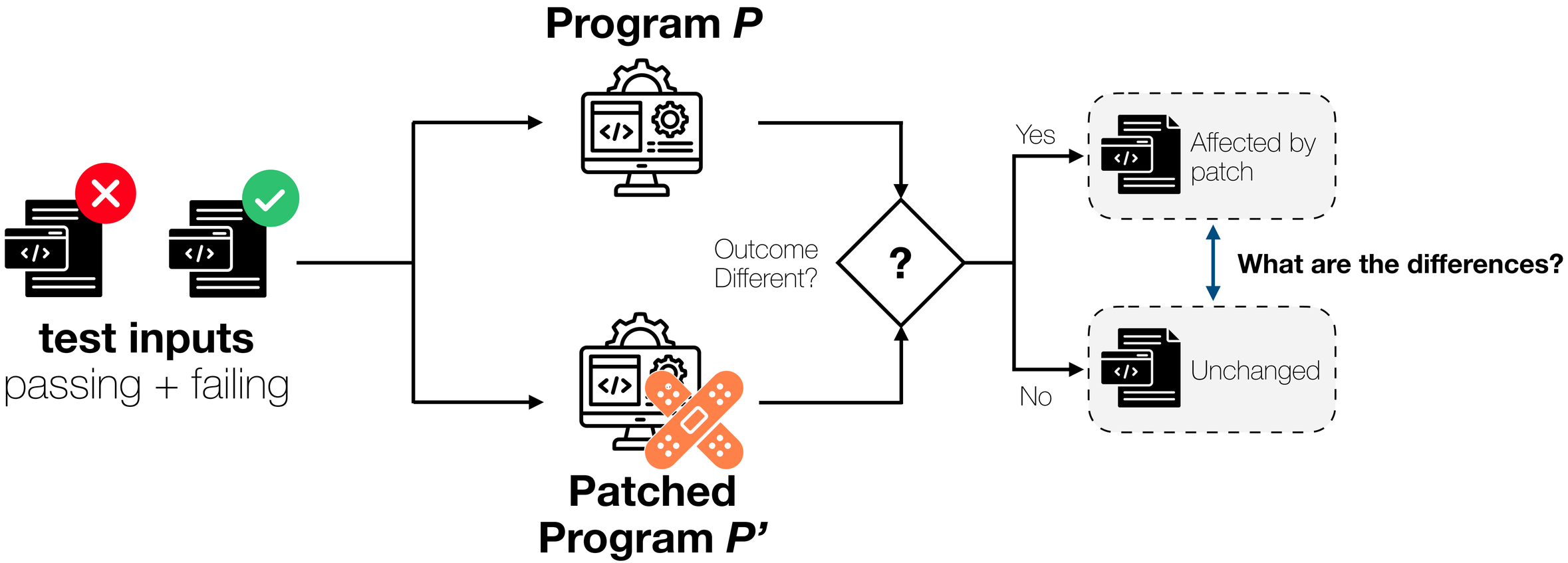
Why is this crucial?

- Developers must be certain about patch boundaries to ensure reliability.
- Blind trust in APR tools or LLM-generated fixes could lead to unforeseen consequences and software failures.

Developer

Automatic Explanations

Differential Behavior



Example

```
1  import math
2
3  def logarithm(x: float):
4      return math.log(x)
```

Fig. 2. A simple function computing the natural logarithm of a number x. While straightforward, it does not handle edge cases such as negative values, leading to errors.

output

P


logarithm(10)


logarithm(-34)


logarithm(-1521)

Example

```python
import math

def logarithm(x: float):
    return math.log(x)
```

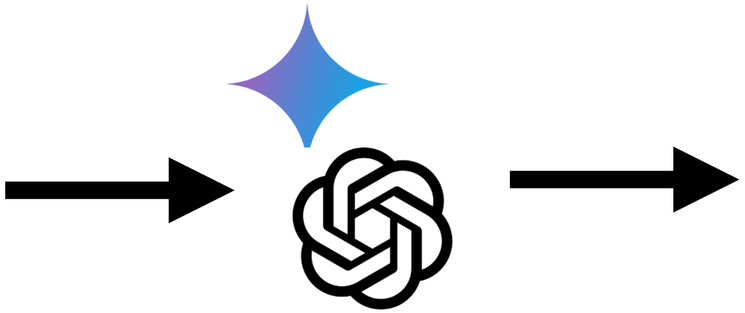
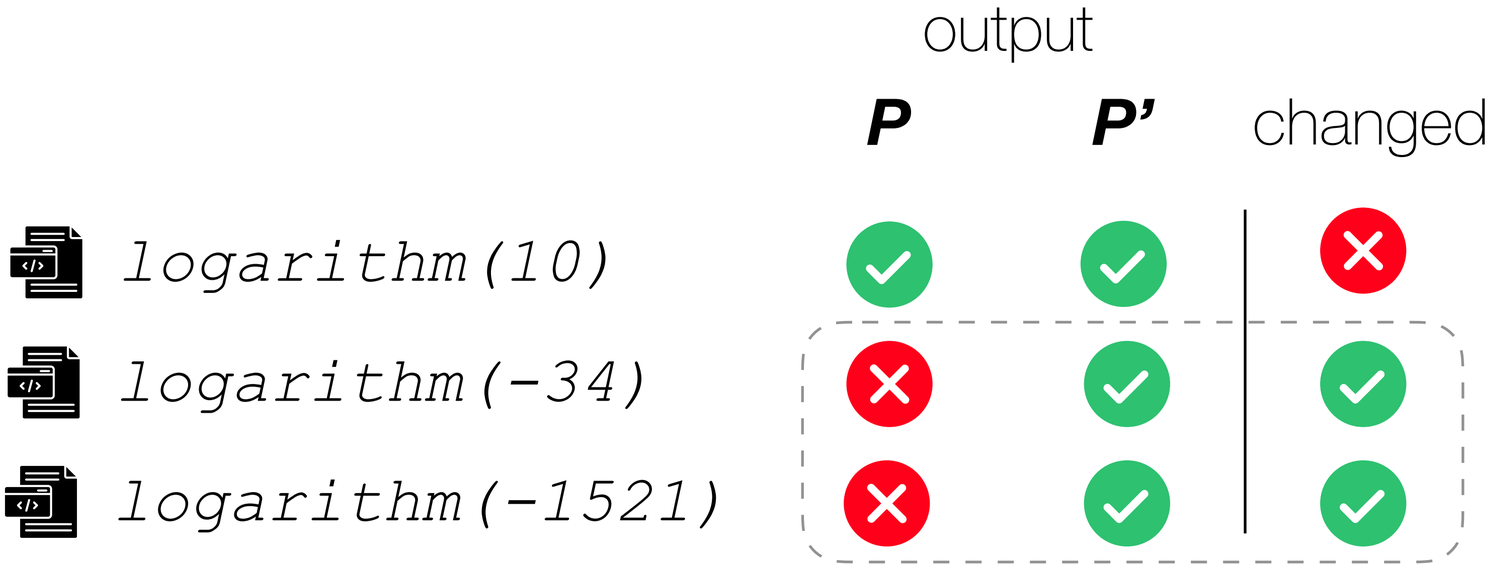


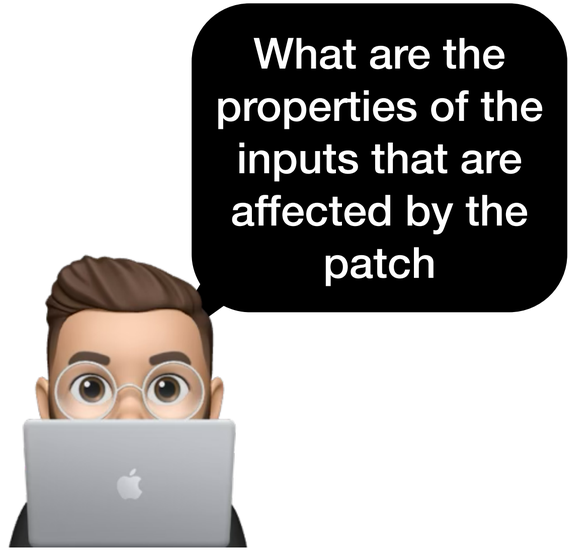
Fig. 2. A simple function computing the natural logarithm of a number x. While straightforward, it does not handle edge cases such as negative values, leading to errors.

```python
import math

def logarithm(x: float):
    # Patch applied to cover edge cases
    if x == 0:
        return float("-inf")
    elif x > 0:
        return math.log(x)
    else:
        raise TypeError("Input must be a" \
                        "positive value")
```

Fig. 3. Patched logarithmic function. It explicitly checks for zero and negative numbers. These changes ensure robust handling of edge cases.





Automatic Explanations

Generating explanations to describe the input properties affected by a patch

Automatic Explanations

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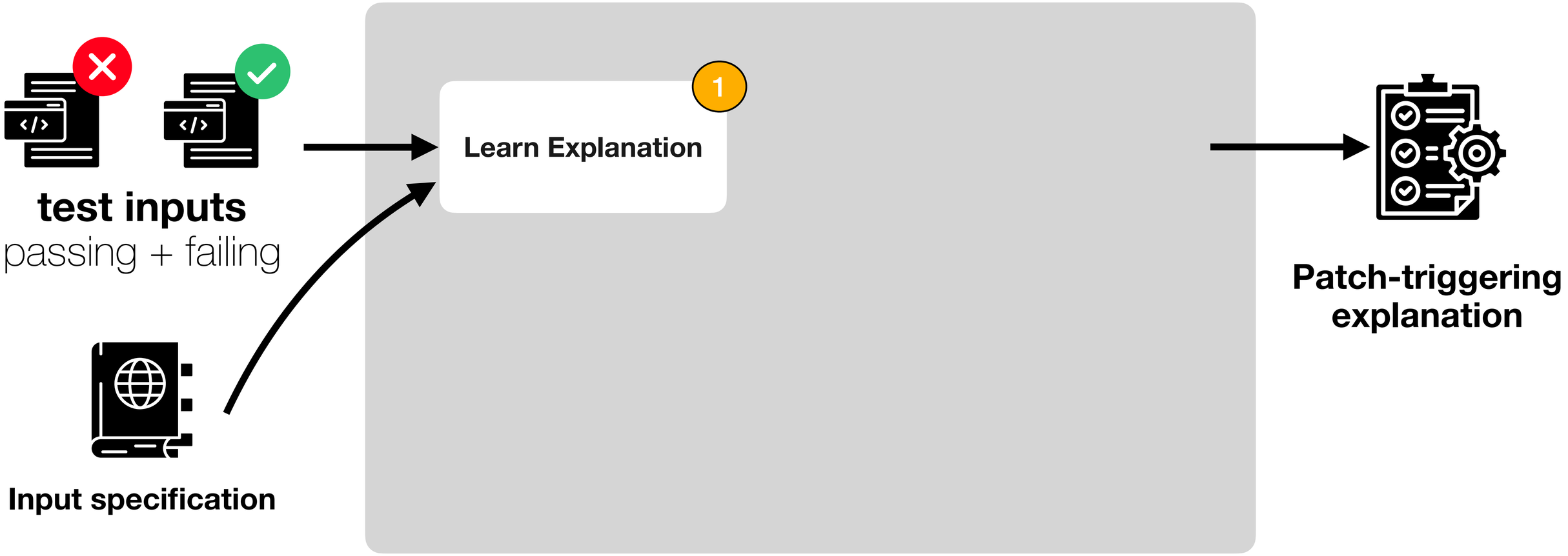

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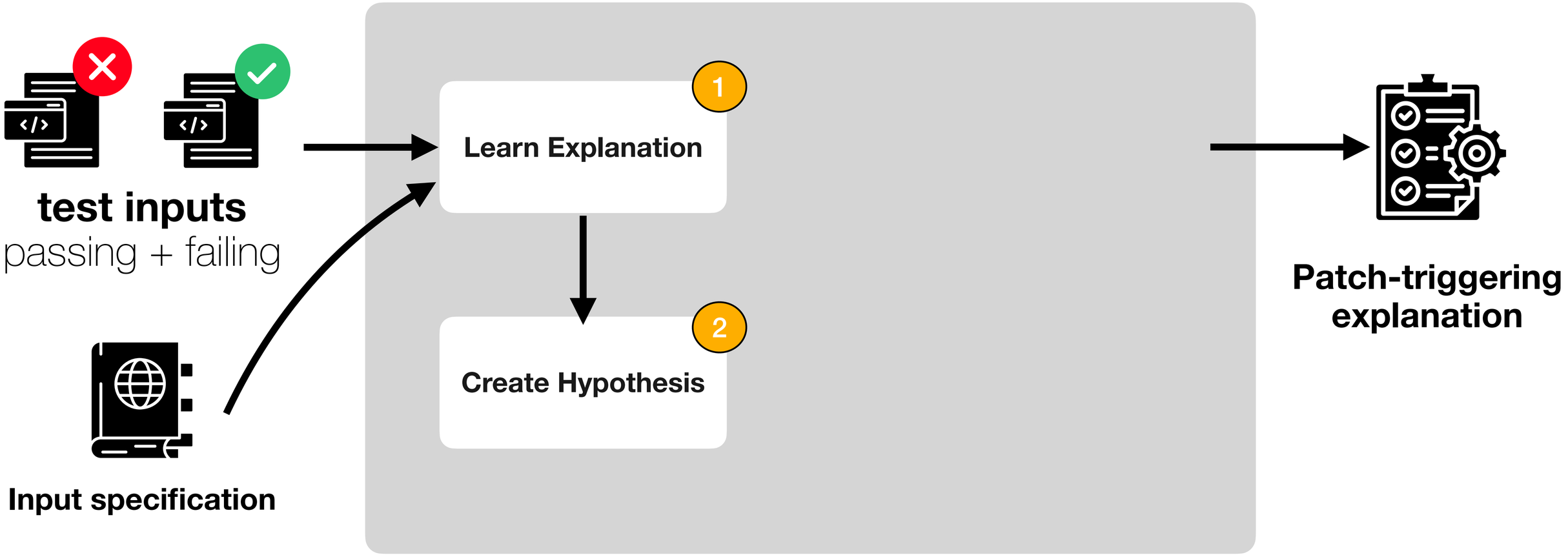

Automatic Explanations

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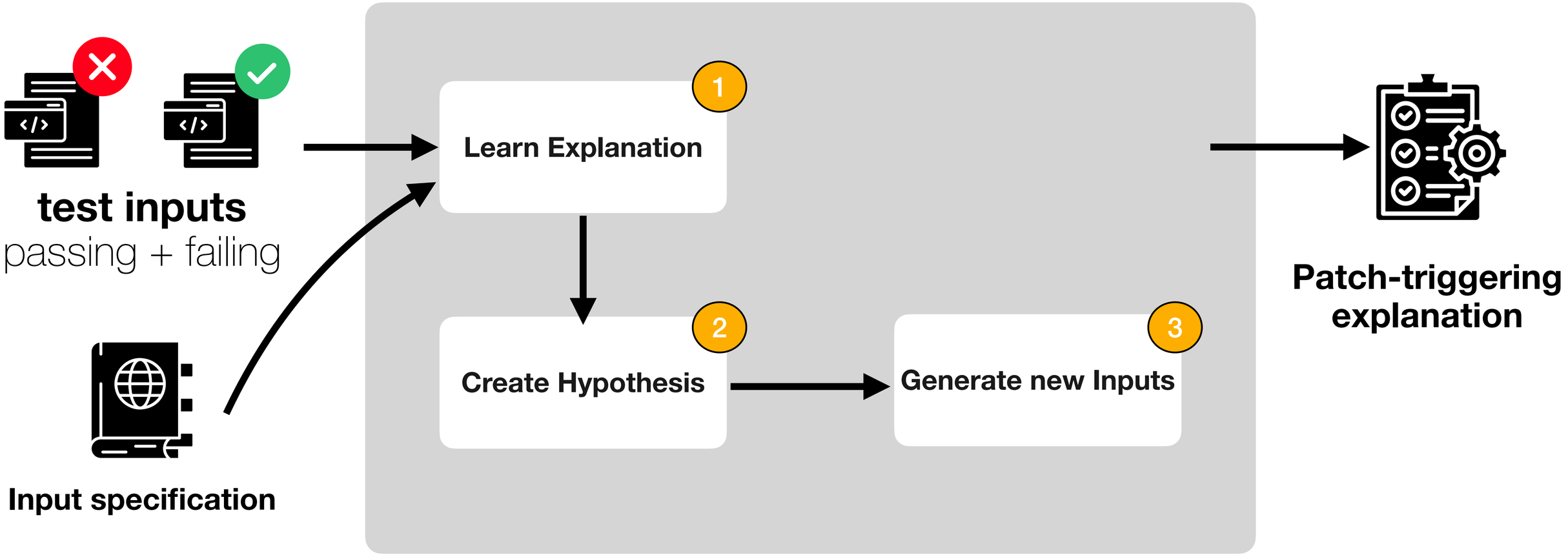

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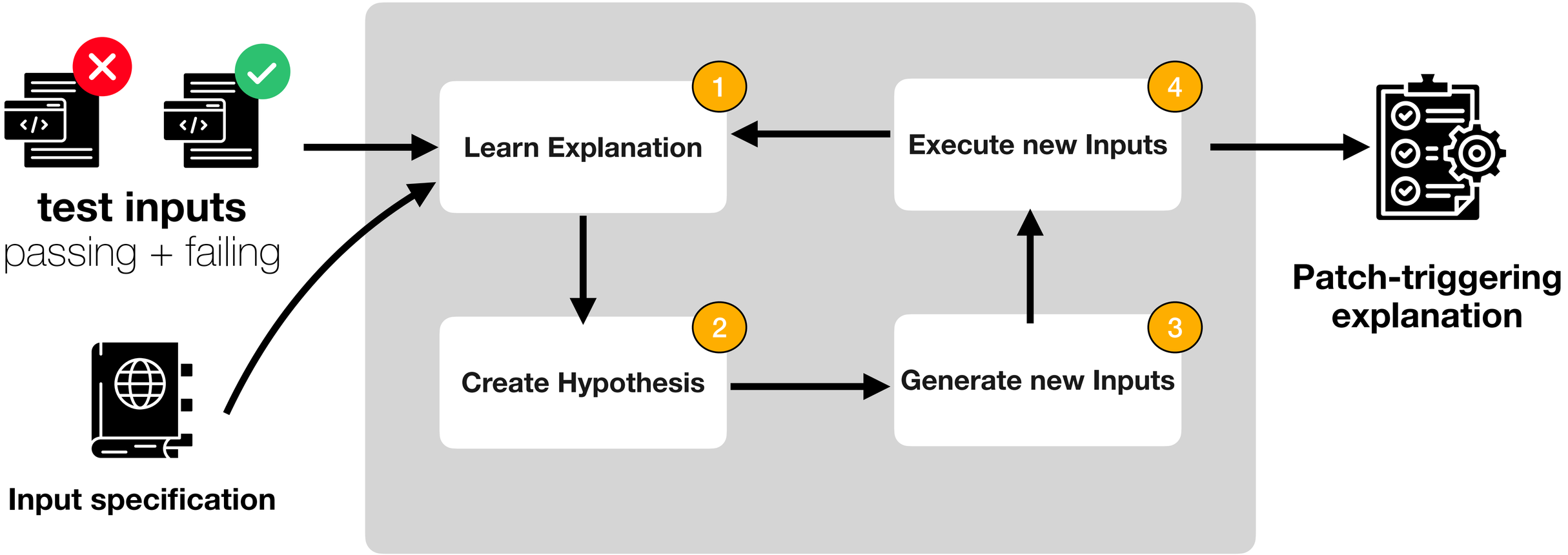
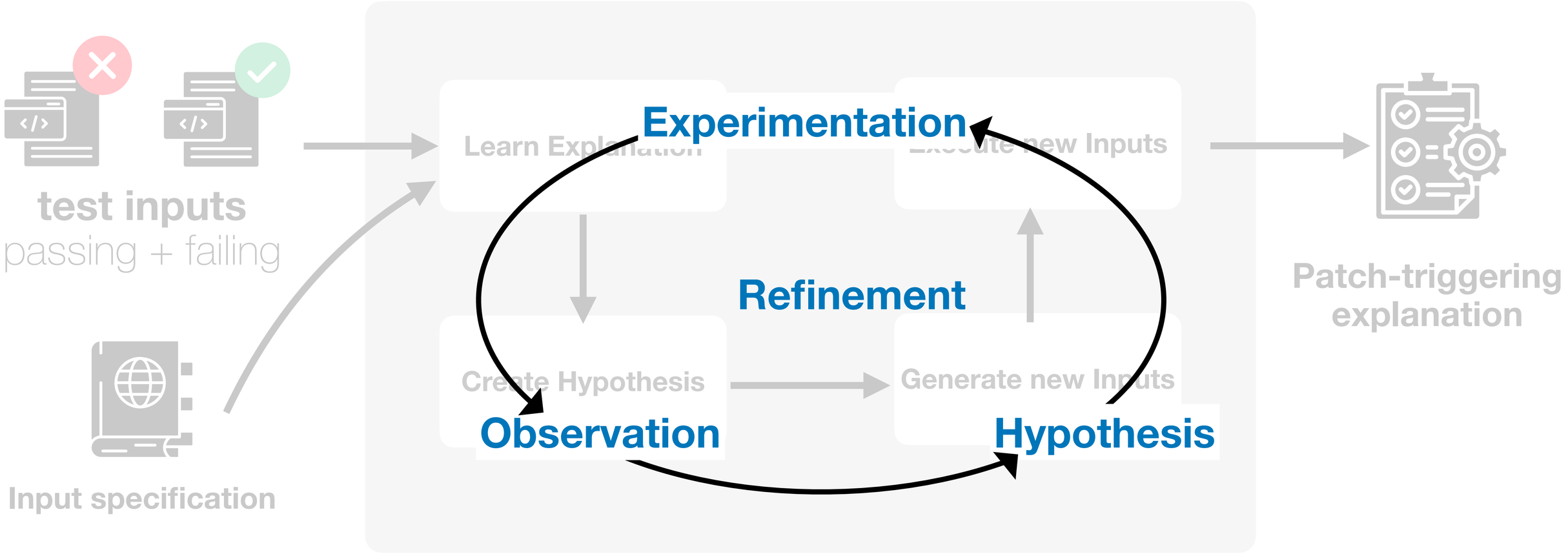


Automatic Explanations

Scientific Debugging



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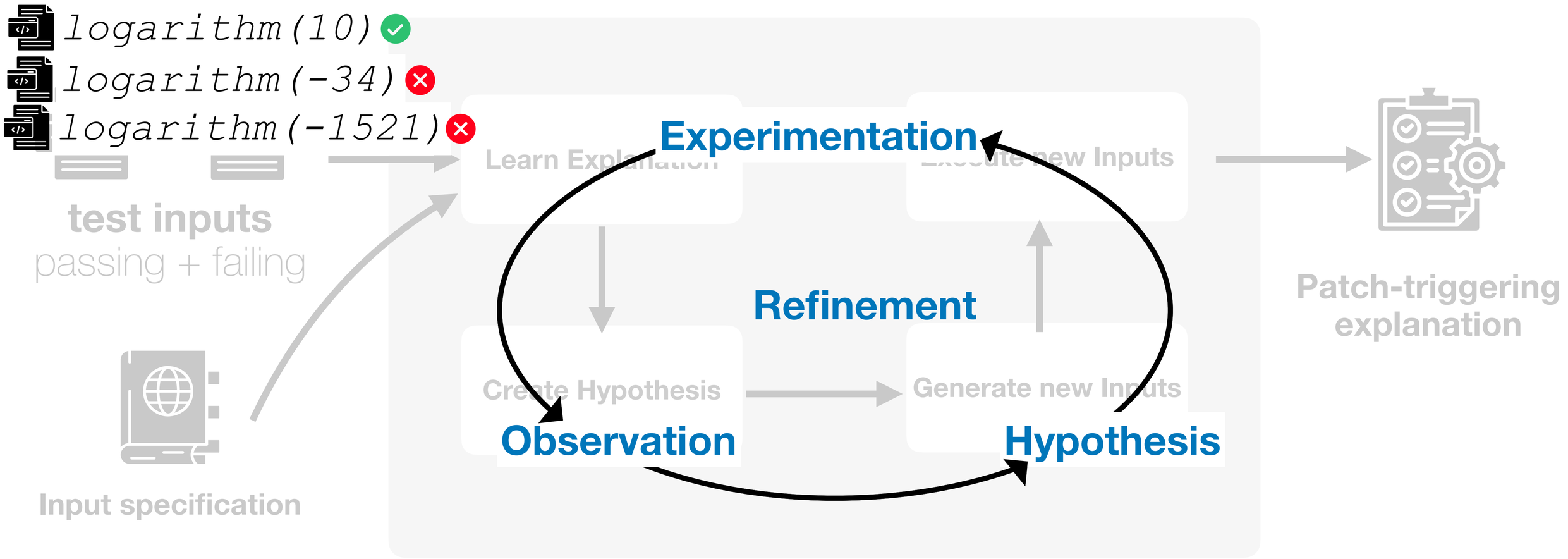

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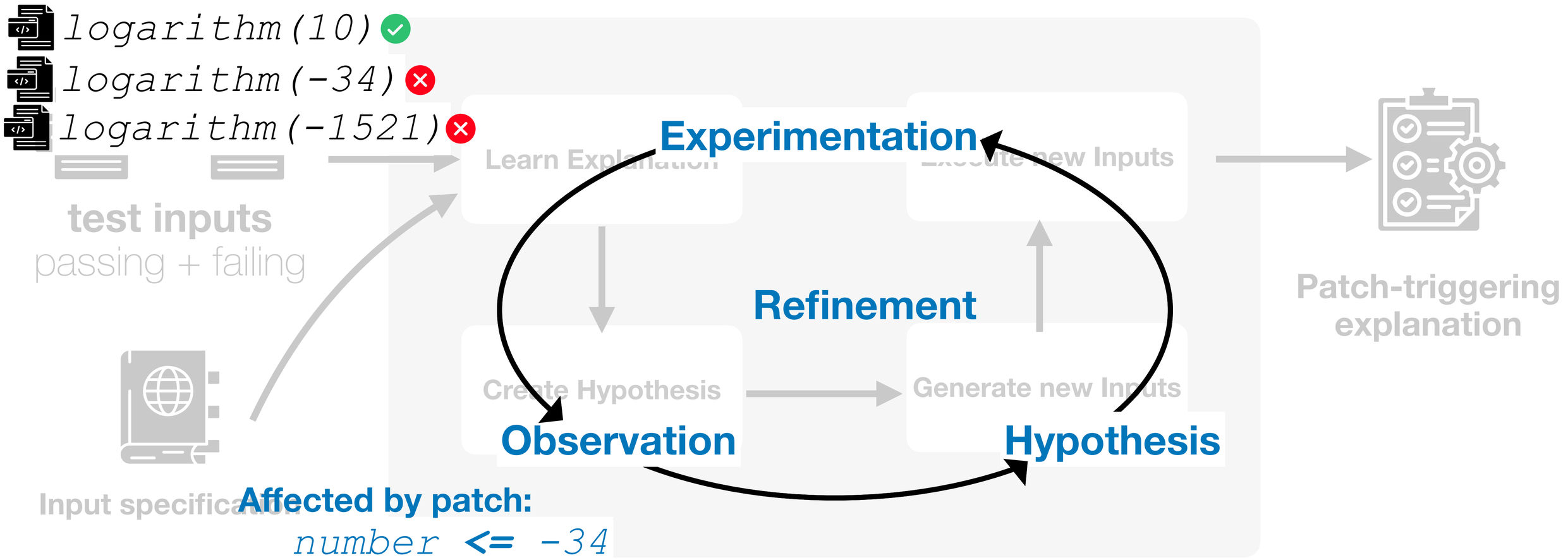

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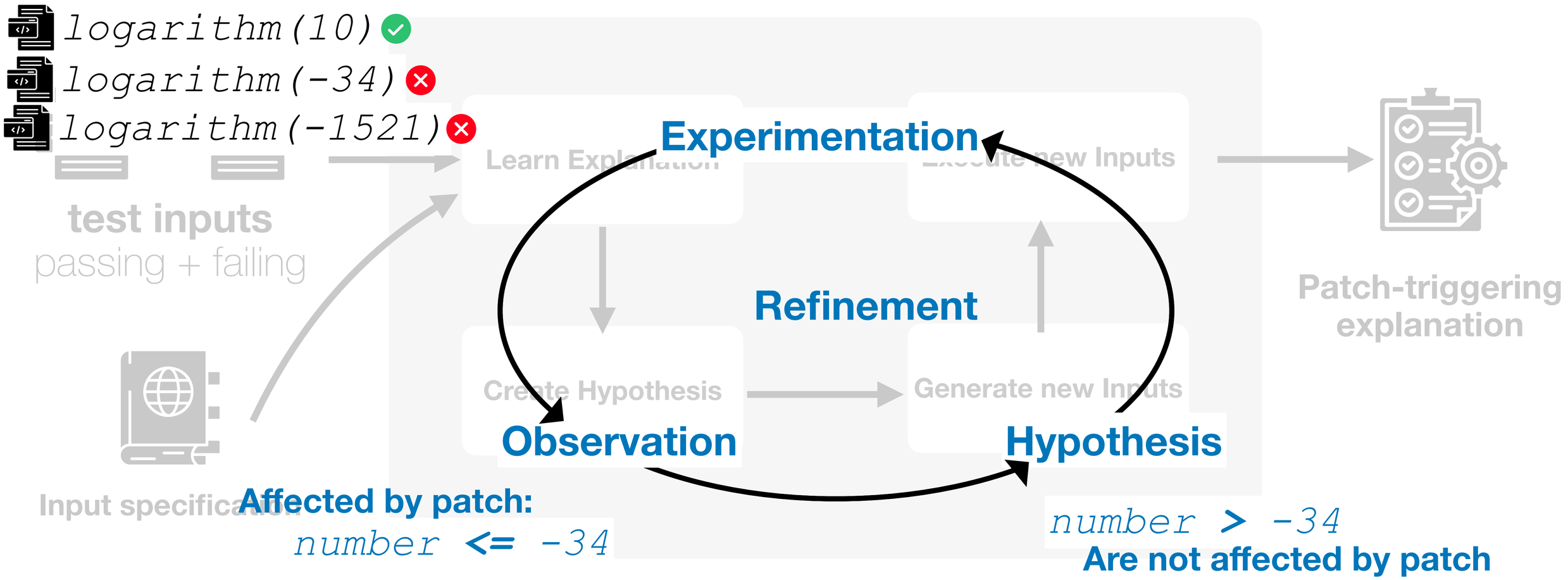

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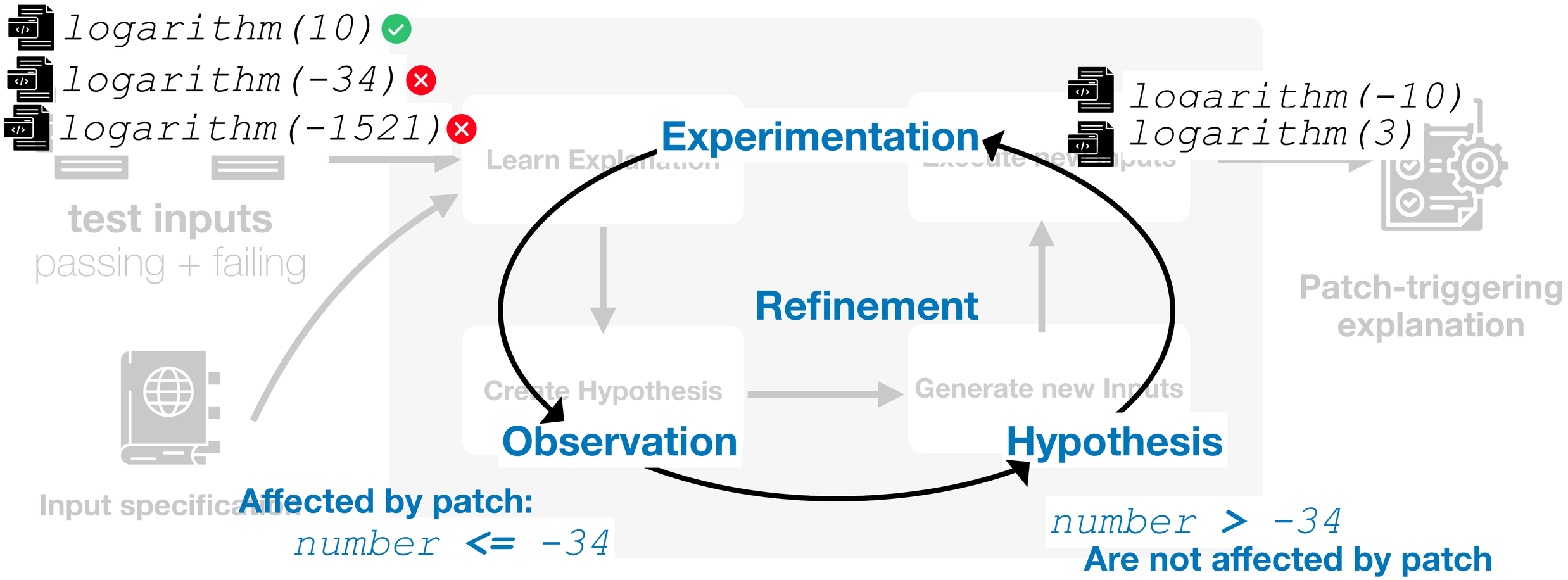

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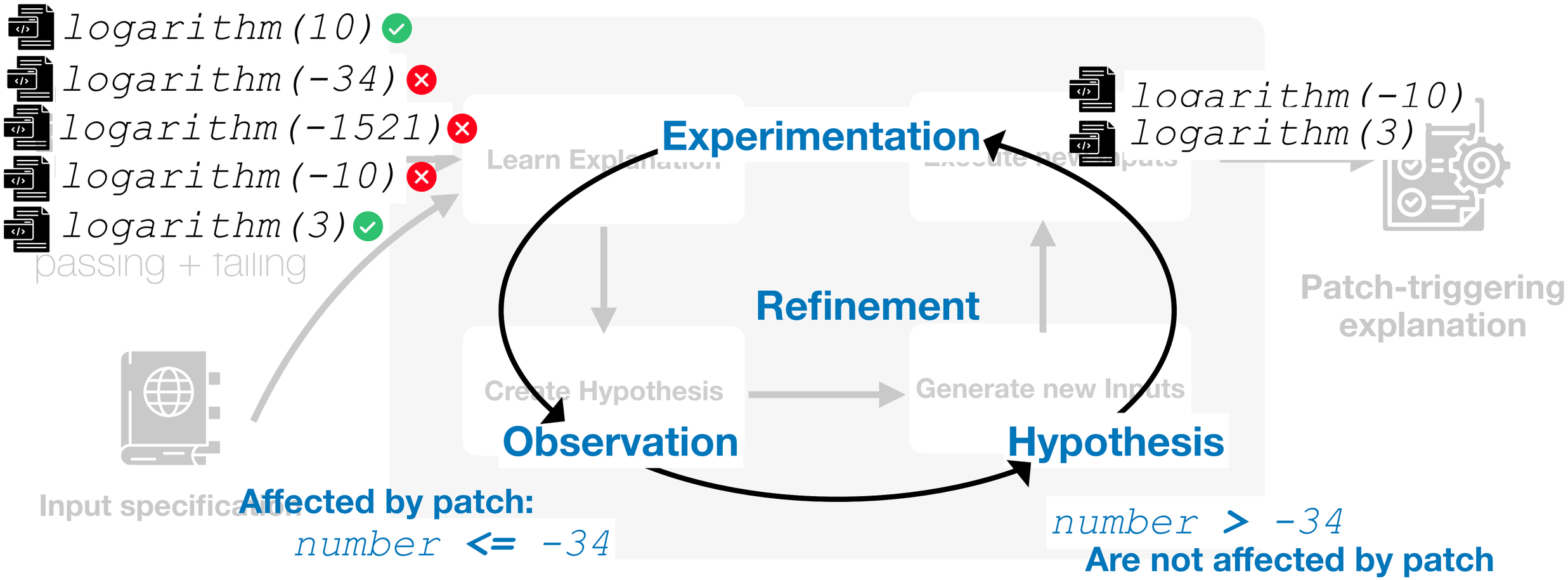

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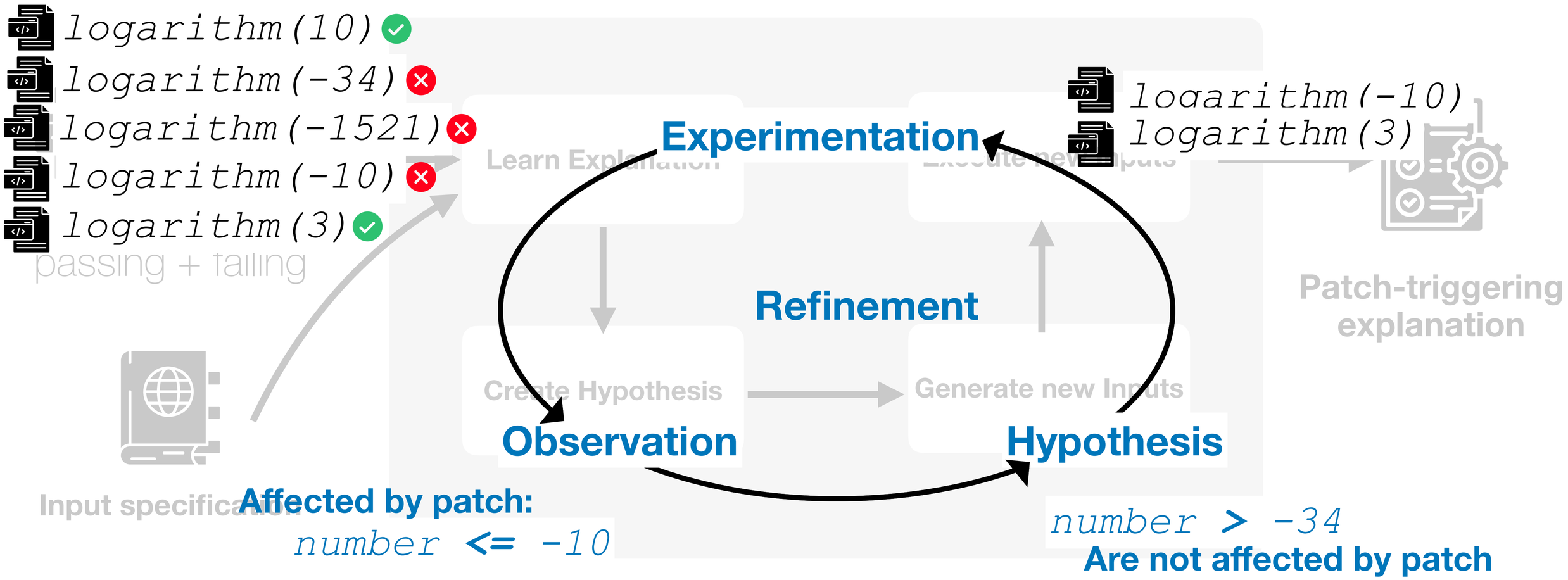

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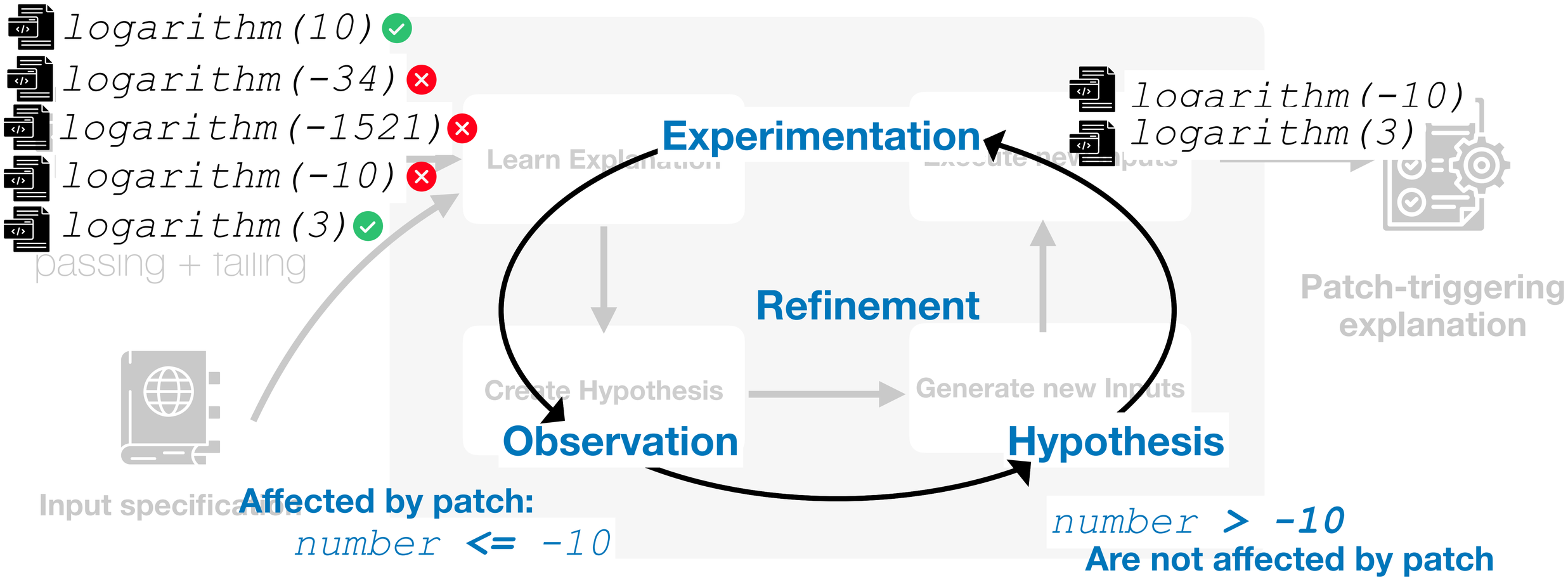

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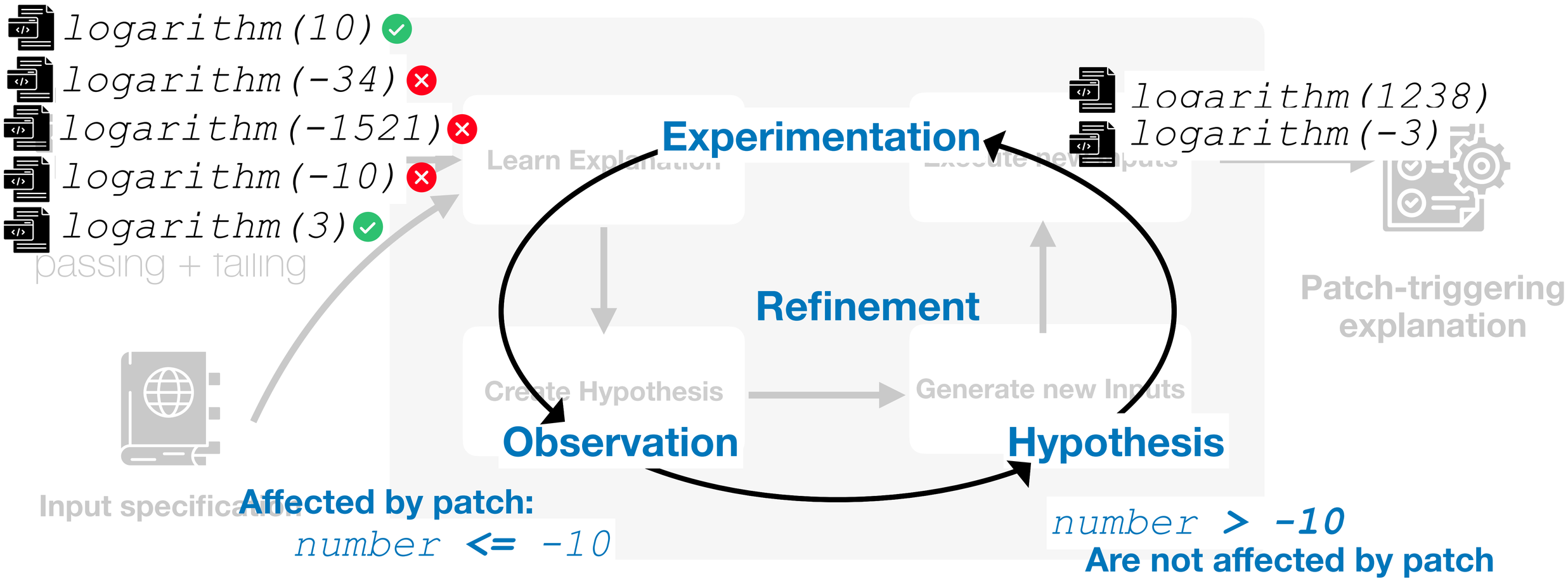

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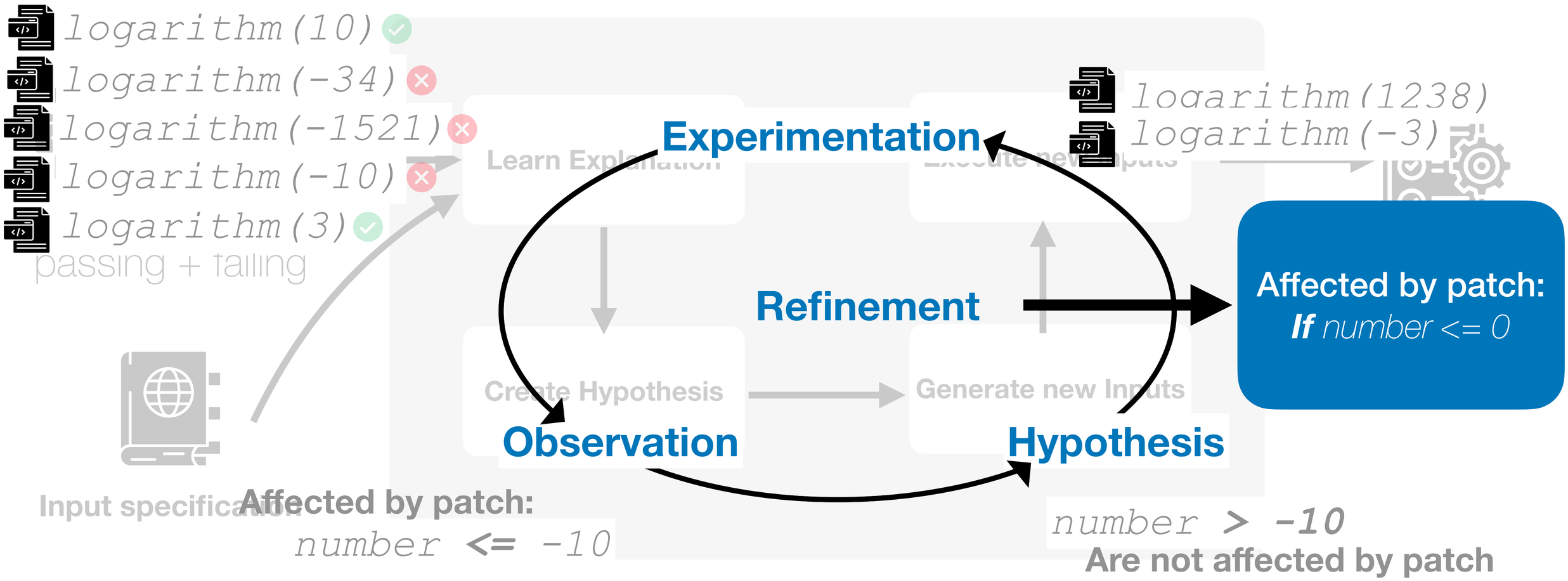

Benchmark Results

RQ1: Predictor

How accurately can the explanations predict whether an input belongs to the input space affected by the patch?

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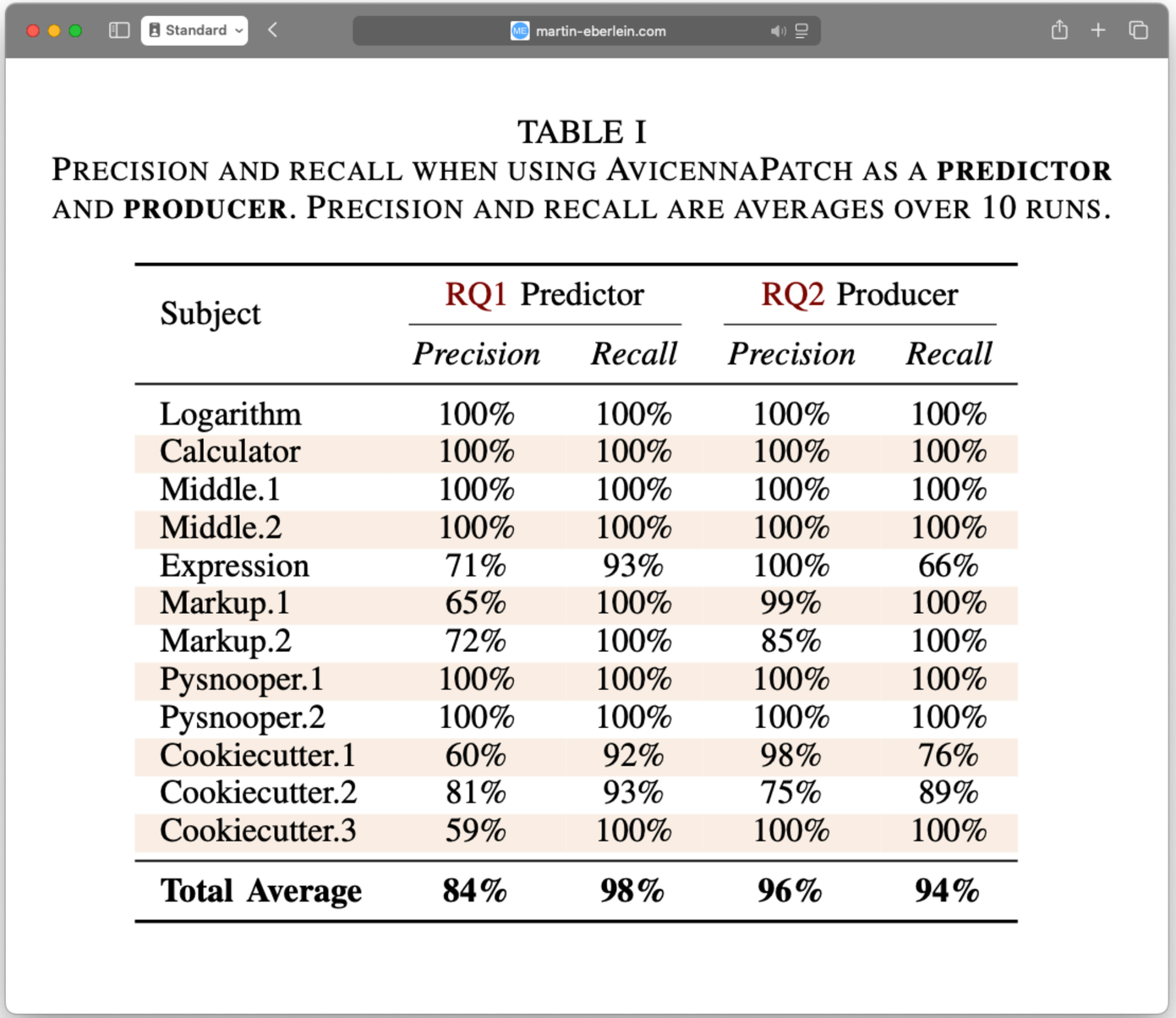

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Subject	RQ1 Predictor		RQ2 Producer	
	Precision	*Recall*	*Precision*	*Recall*
Logarithm	100%	100%	100%	100%
Calculator	100%	100%	100%	100%
Middle.1	100%	100%	100%	100%
Middle.2	100%	100%	100%	100%
Expression	71%	93%	100%	66%
Markup.1	65%	100%	99%	100%
Markup.2	72%	100%	85%	100%
Pysnooper.1	100%	100%	100%	100%
Pysnooper.2	100%	100%	100%	100%
Cookiecutter.1	60%	92%	98%	76%
Cookiecutter.2	81%	93%	75%	89%
Cookiecutter.3	59%	100%	100%	100%
Total Average	**84%**	**98%**	**96%**	**94%**

Limitations

Vocabulary & Pattern Catalogue

Reliance on an appropriate vocabulary to express the conditions under which a patch is triggered.

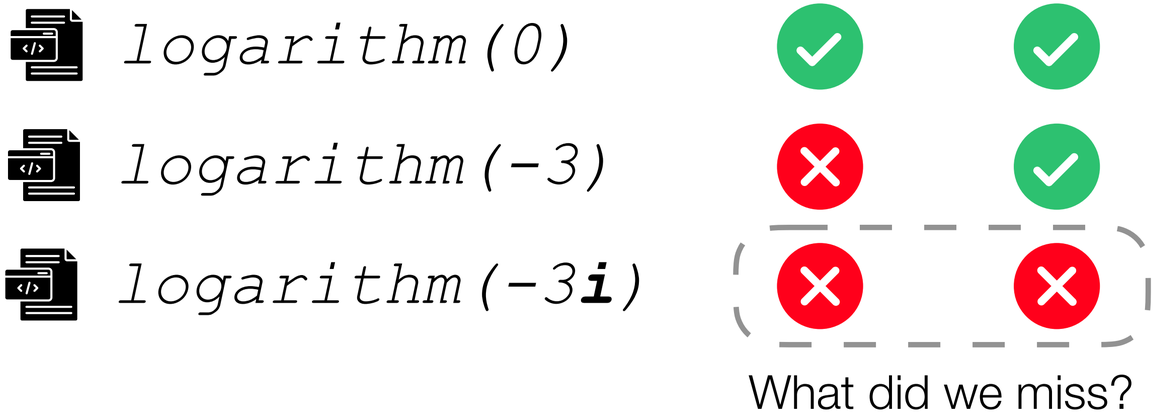
Requires Grammar/Specifaction

Explanations are constructed based on the provided grammar. Grammars may not always be available.

Next Steps?

Partial and Incomplete Patches

Extended to identify partial or incomplete patches by analyzing the properties of failing inputs unaffected by the patch



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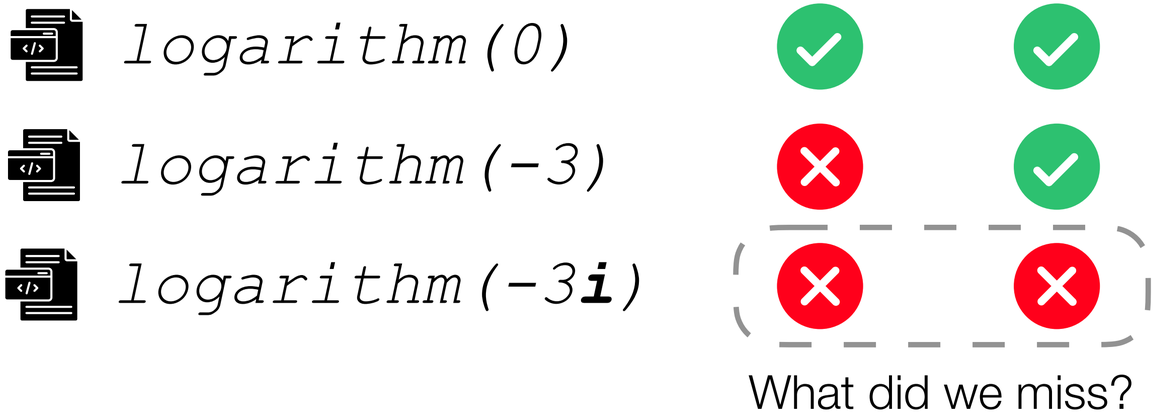

Integration with Symbolic Execution

Can the explanations be used to guide symbolic/concolic execution techniques?

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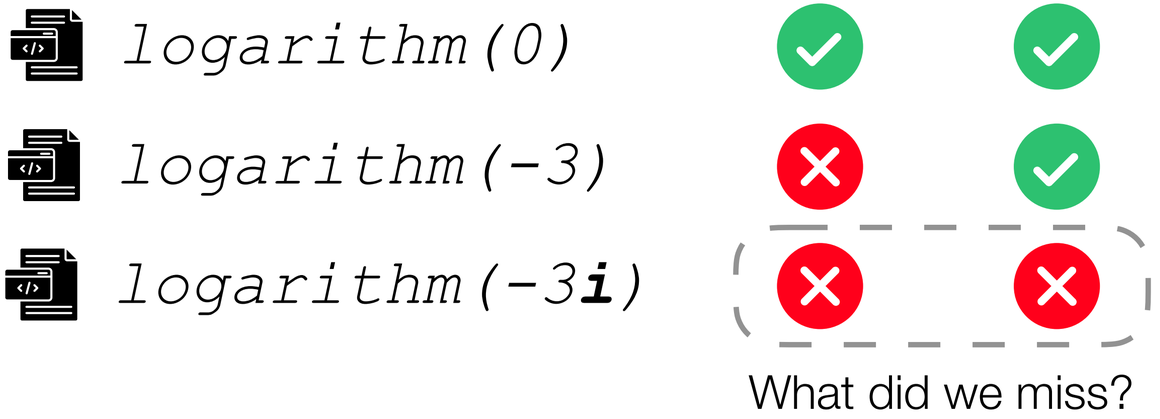

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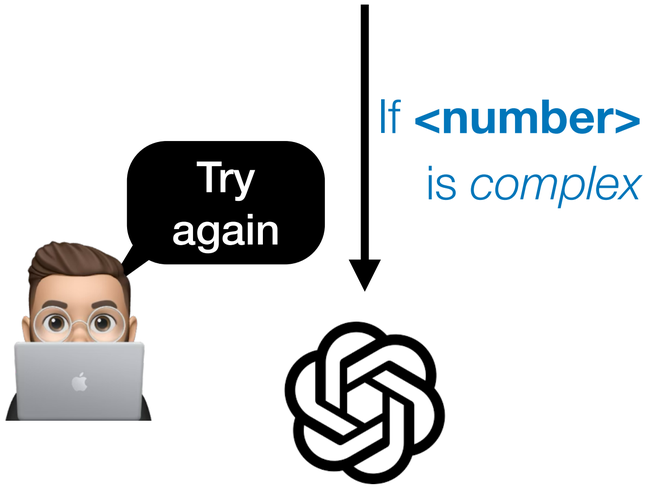
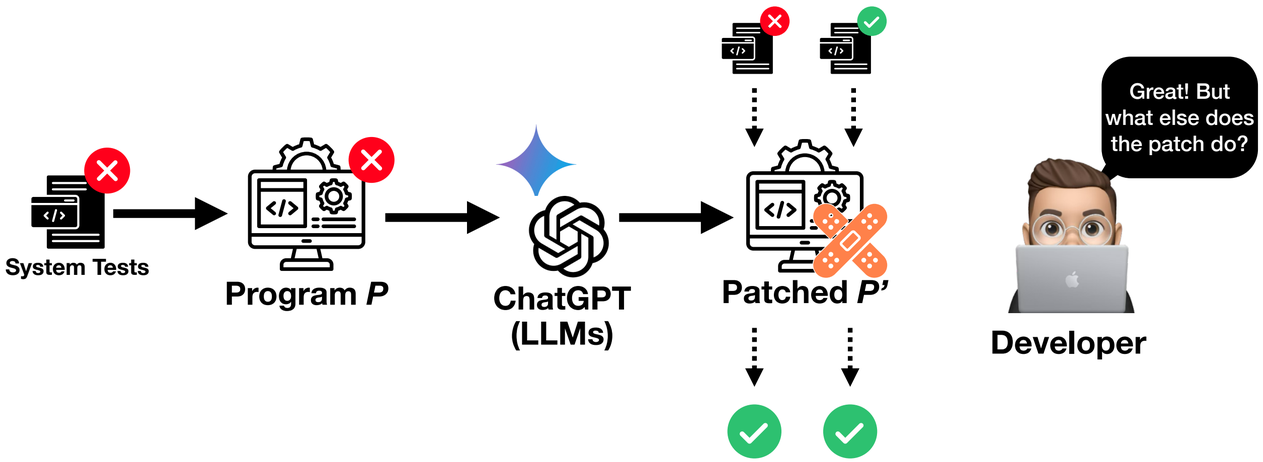


Additional Applications Scenarios

Automated Program Repair & Guide LLMs

Trust Issues?

Would you trust a patch generated by ChatGPT to fix your critical code?



3

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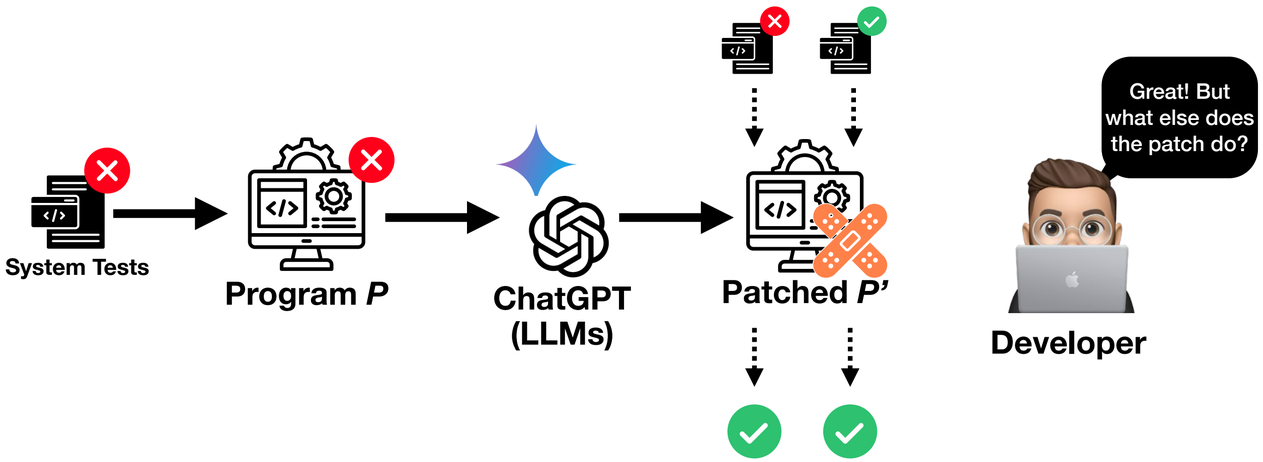
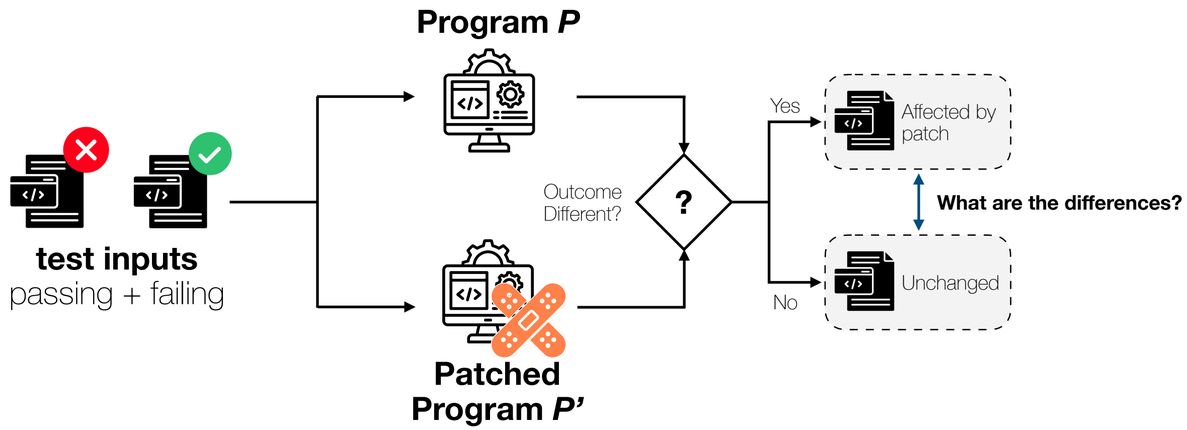


Automatic Explanations

Differential Behavior



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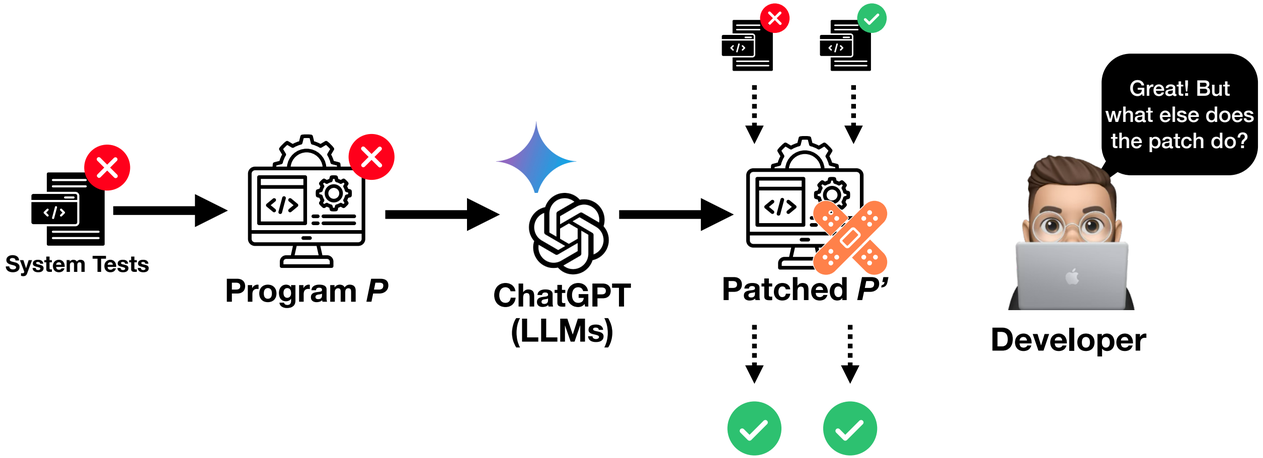

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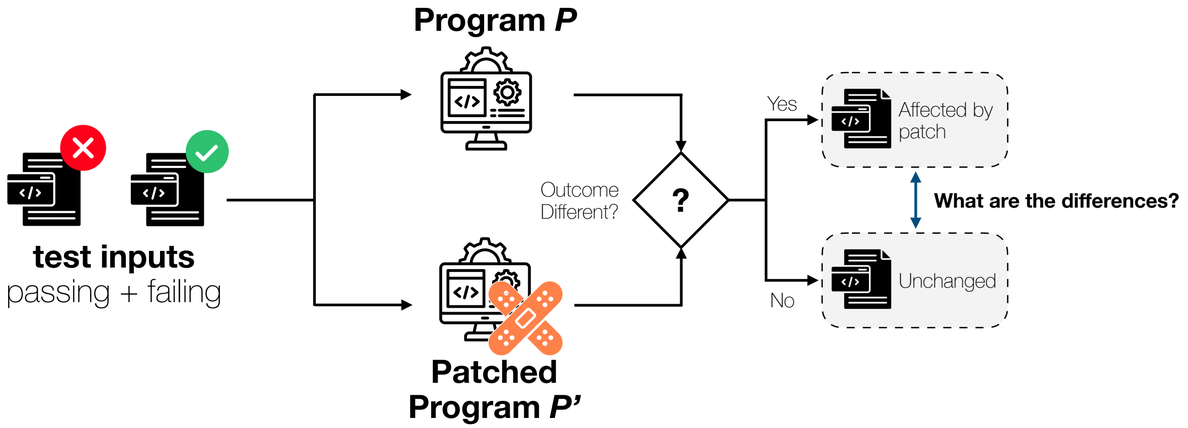

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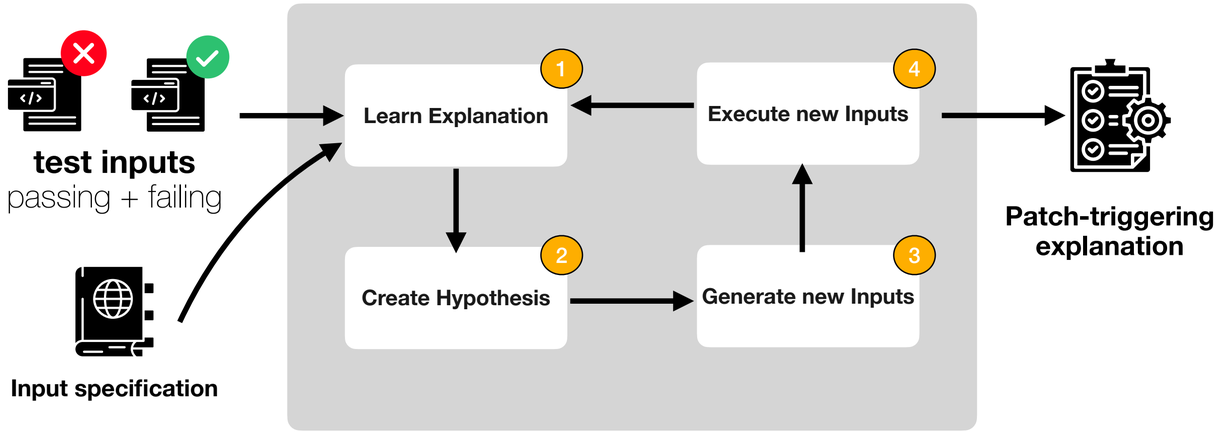

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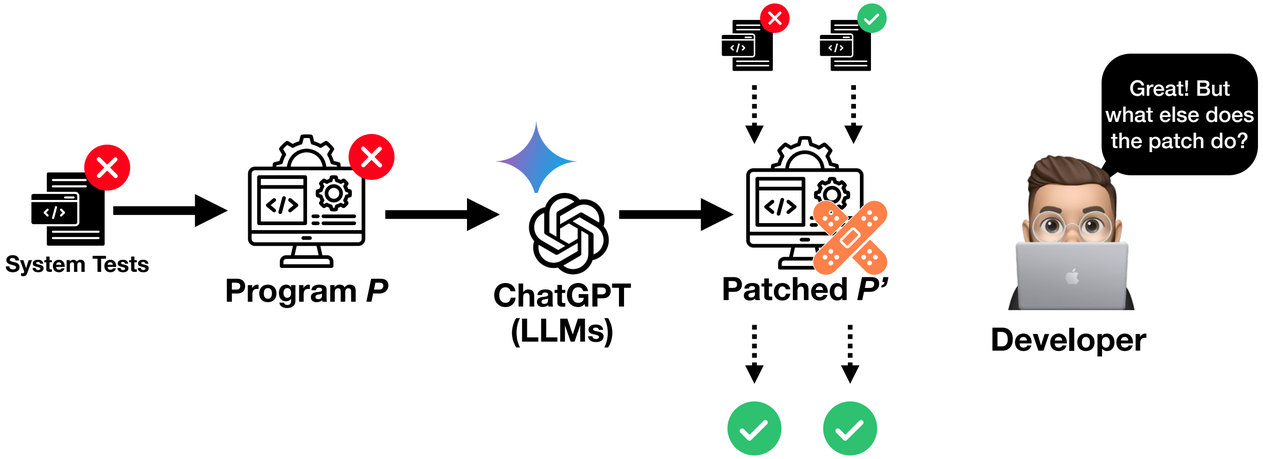

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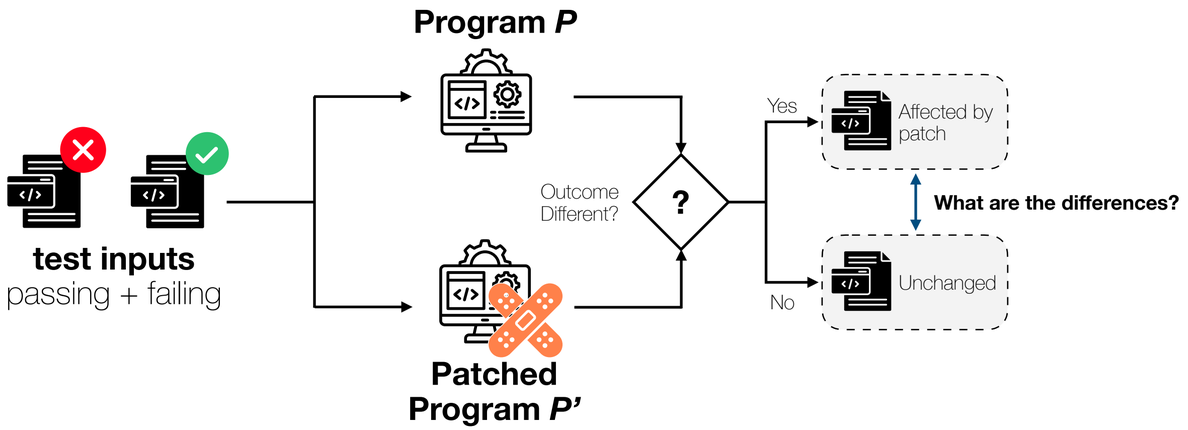

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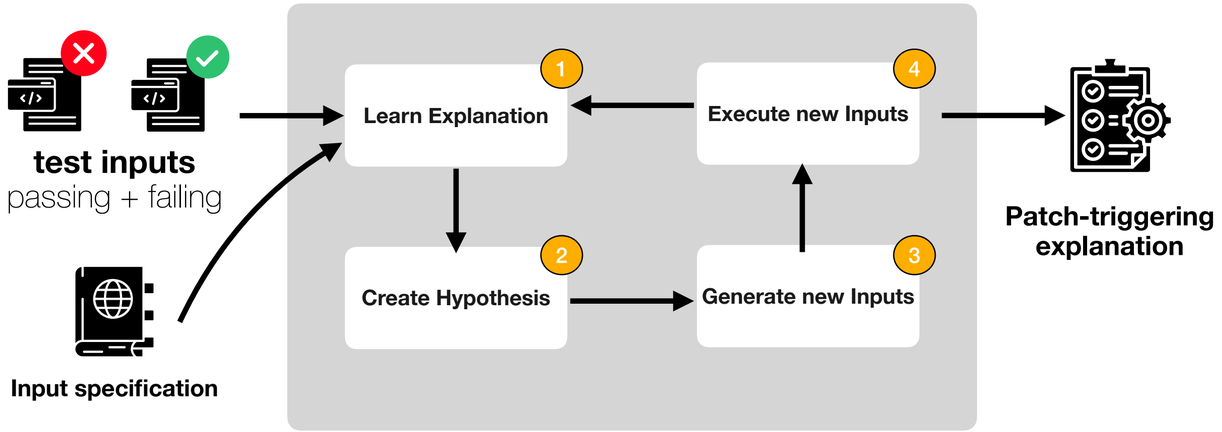

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Contact

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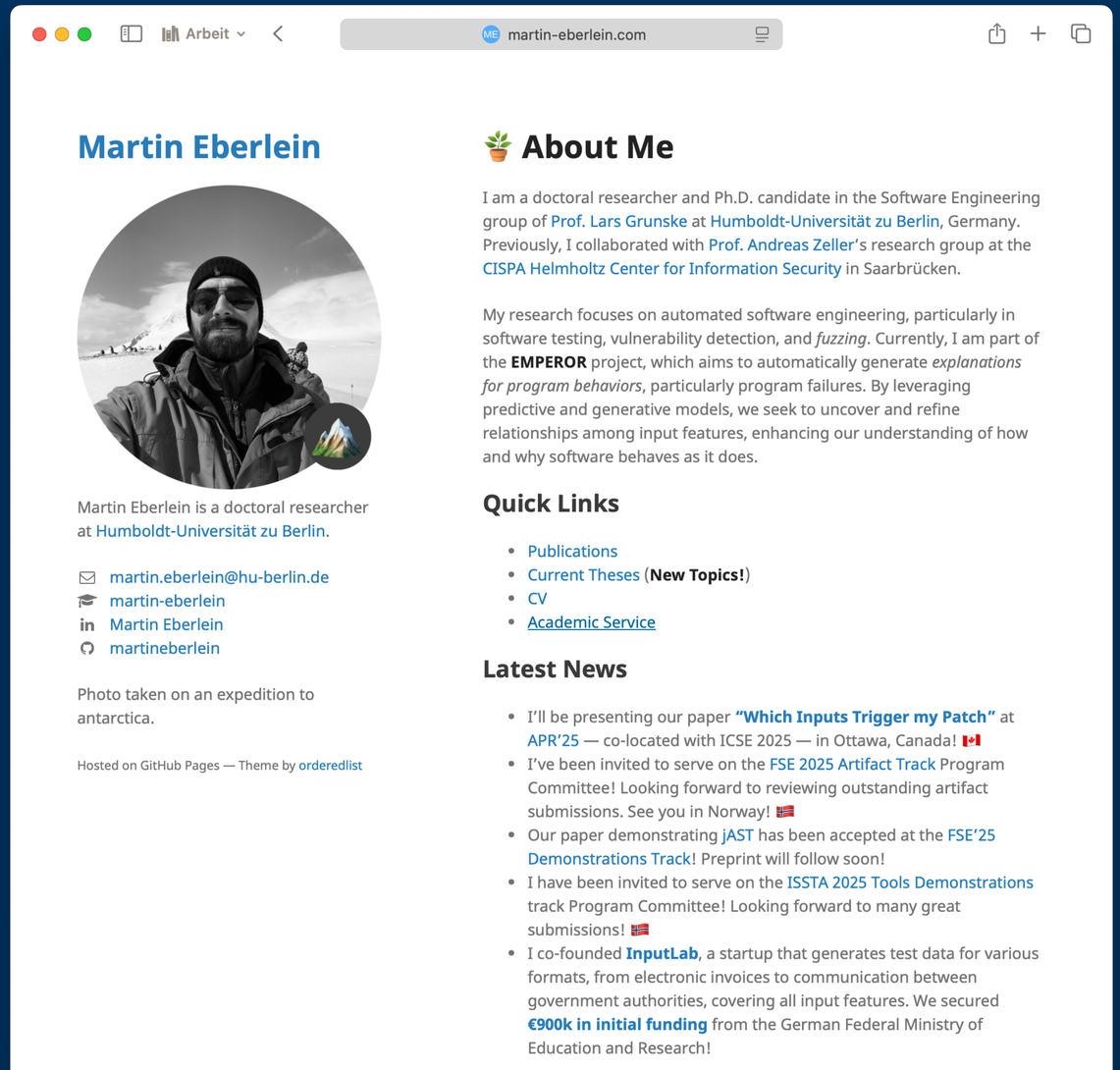
Martin Eberlein



Describing Input Properties

Input Specification Language

Input Specification Language

„Input Invariants“: Dominic Steinhöfel & Andreas Zeller, ESEC/FSE 2022

Syntax
Input Grammar

```
⟨heartbeat-request⟩ ::= 0x1 ⟨length⟩ ⟨payload⟩ ⟨padding⟩

⟨heartbeat-response⟩ ::= 0x2 ⟨length⟩ ⟨payload⟩ ⟨padding⟩

⟨length⟩ ::= ⟨uint16⟩

⟨payload⟩ ::= ε | ⟨byte⟩ ⟨payload⟩

⟨padding⟩ ::= ε | ⟨byte⟩ ⟨padding⟩
```

Semantics
ISLa Constraints

```
int(⟨length⟩) <= 7

len(⟨payload⟩) ≠ 9

int(⟨length⟩) > len(⟨payload⟩)
```