Automating Software Debugging: An Approach to Travel Back to The Root Cause of Your Bug

Presenter: Hongshu Wang

Introduction

Project Objectives

Data Dependency Recovery

- Address the problem of missing data dependencies in the current tools
  - Exploration of Potential Approaches
  - Solution Design and Implementation
  - Experiment Design and Conduction

Contributions to DebugPilot

- Accomplish a research work that automates the debugging process through a time-travelling approach
  - Theory Refinement
  - Experiment Conduction

Background

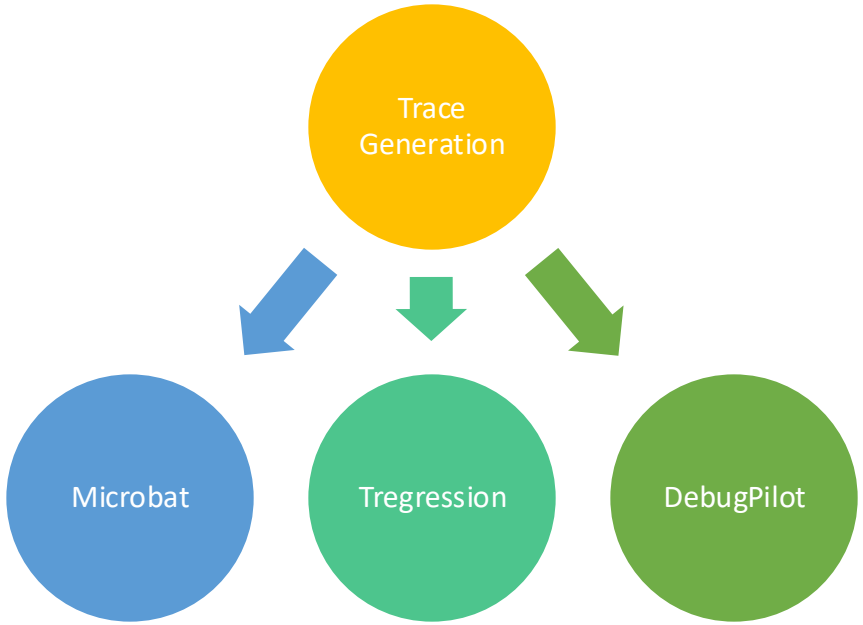
Back-tracking: Agrawal et al., 1993

- Working backwards from the fault-revealing step.
- **Dynamic slicing** can identify the data and control dominance relations of an execution step.

Background

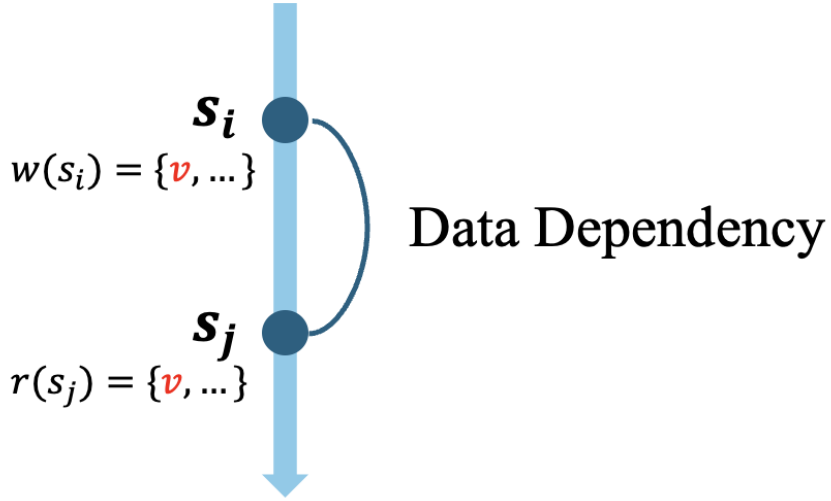
Tools

- Common step: One or more execution traces with causality relations are generated.
- Microbat
  - The users can search for the root cause by providing feedback to the steps.
- Tregression
  - The buggy and fixed versions of traces are aligned.
- DebugPilot
  - A possible debugging process is generated based on the suspiciousness.



Data Dependency Recovery

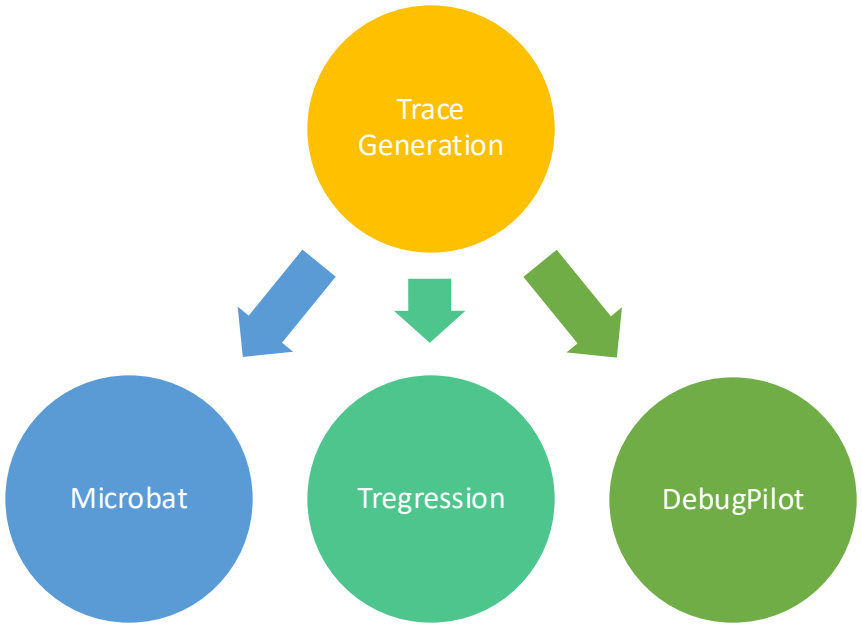
Definitions



- Data Domination
  - Data Dominator: s_i
  - Data Dominatee: s_j
  - Data Dependency: between s_i and s_j
- Critical Variable: v

Problem Statement

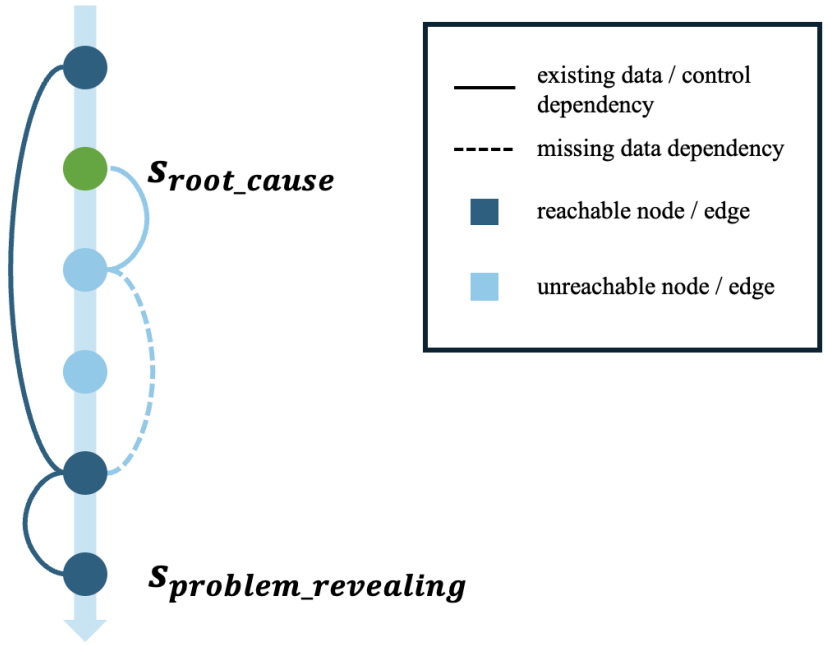
- Existing research works assume that the collected data flows are complete.
- Missing critical variables -> Missing data dependencies
- Two sources of missing critical variables during trace generation:
  - Incomplete Instrumentation
  - Partial Recording of the Variables



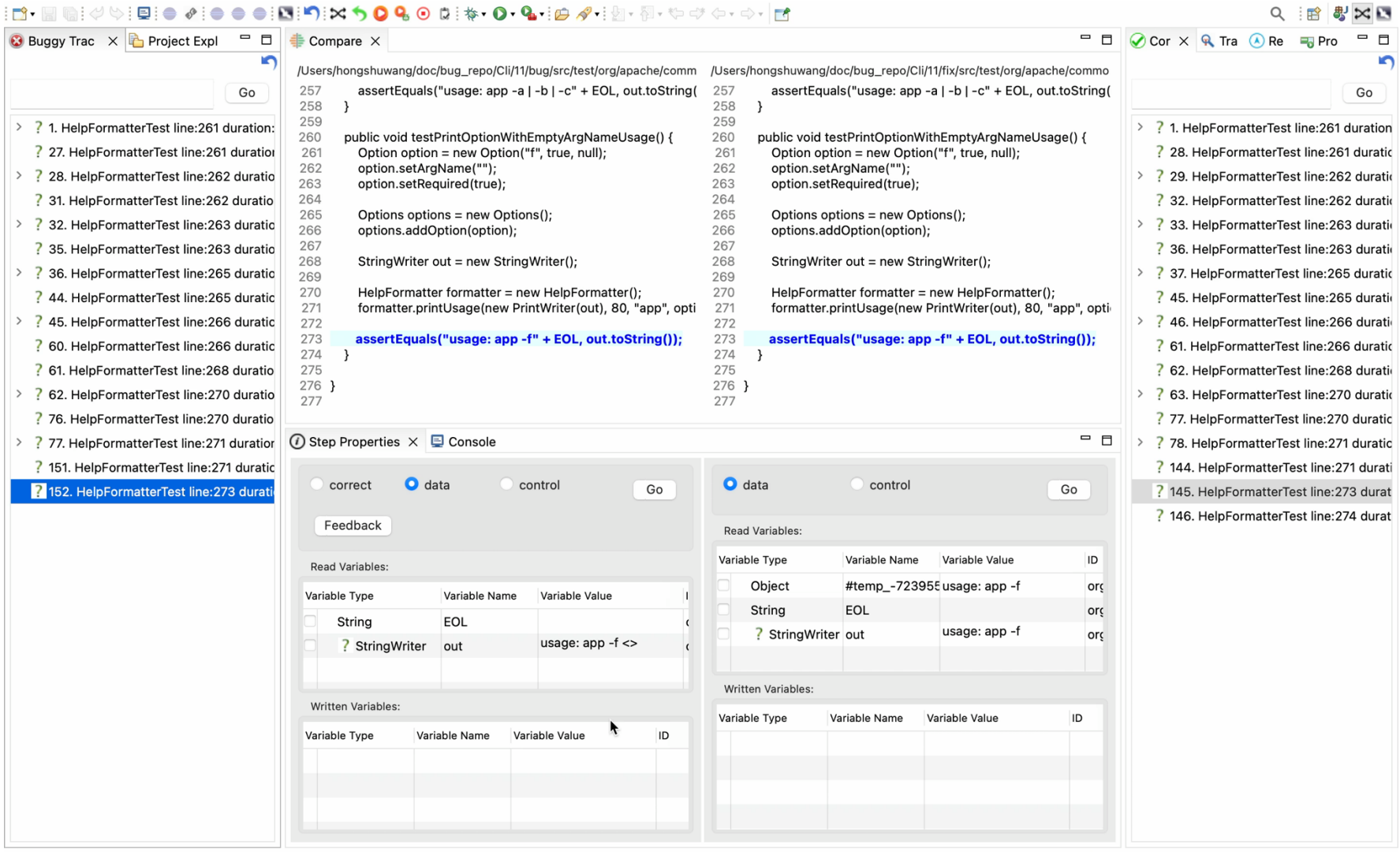
Problem Statement

- Missing data dependencies can break the path from $s_{problem\_revealing}$ to s_{root_cause}.
- Leads to failure in locating the root cause.

Aim: Recover the missing data dependencies through recovering the critical variables.



Motivating Example



Potential Solutions

Comparison of Variables

- **Approach**: compares variable values before and after method invocation
- **Limitations**: needs to record the variable values before method invocation

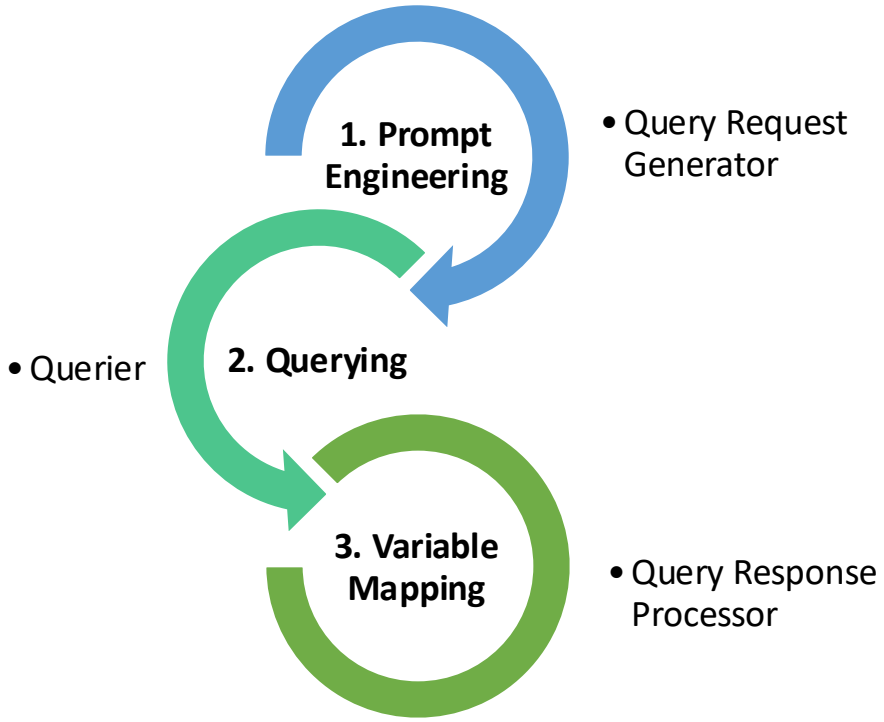
Data Flow Analysis

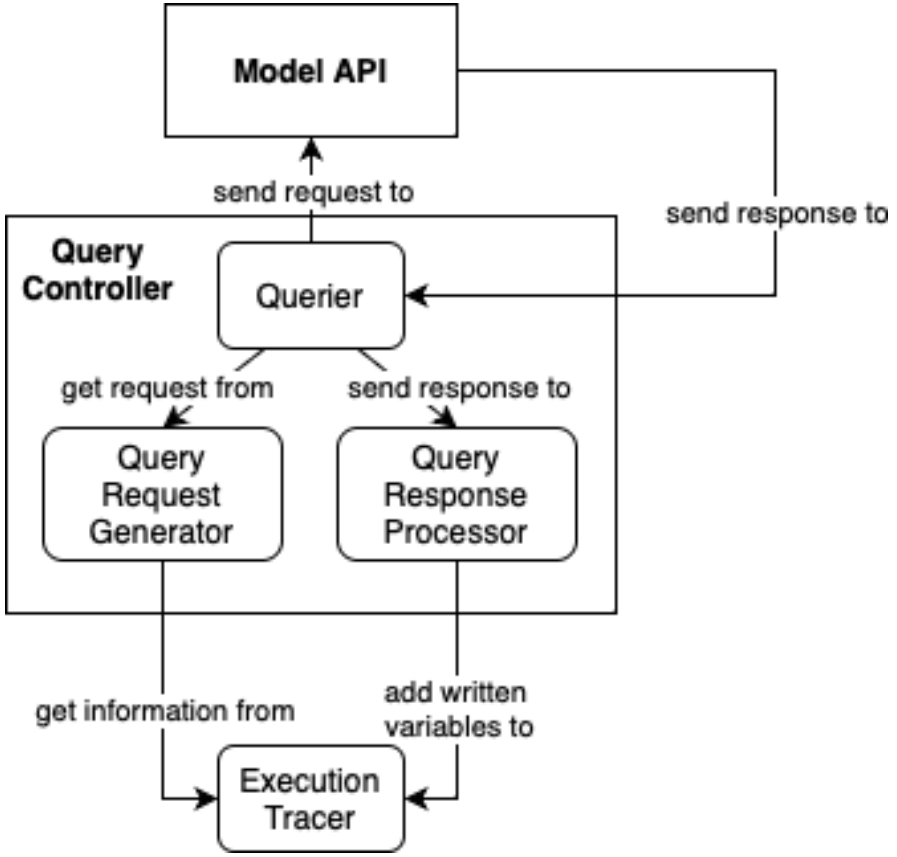
- **Approach**: applies traditional data flow analysis on source code
- **Limitations**:
  - needs to construct extra data structures like AST or PDG
  - time and space complexities are similar to dynamic program analysis

Enhanced Instrumentation

- **Approach**: instruments code in third party libraries
- **Limitations**:
  - runtime overhead for executing the inserted instructions
  - infinite loops during execution

LLM Leveraged Data Dependency Recovery: **Solution Overview**

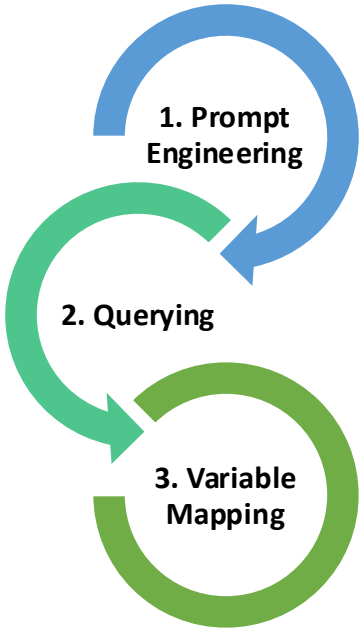




Related Work

- **Capability of LLMs on understanding code syntax and semantics**: Ma et al., 2023
  - Examined the performance of LLMs on completing a series of code analysis tasks, including data dependency analysis.
  - Given a segment of code, the task is to determine whether two variables are “data-dependent”.
  - A large number of queries is required to build a complete data flow in a program.

Solution Version 1



Prompt Engineering (V1)

- Using LLM as a classifier
- Common data structures in Java use an internal array to store the elements
- Query Response Format:
  - $< method\ type >< method\ action >< name\ of\ internal\ array >< index >$
  - method type: get / set
  - method action: add / remove / replace
  - index: start / end / all / index / key
- e.g. ArrayList<T> # add(T object)
  - $< set >< add >< elementData >< end >$

Solution Version 1

Prompt Format (V1)

“

Return in the following format: {Query Response format}

{Explanation of meanings of the tags in the response}

For example:

{method 1} with signature {signature 1}:<response 1>

{method 2} with signature {signature 2}:<response 2>

…

Then {method queried} with signature {signature queried}:

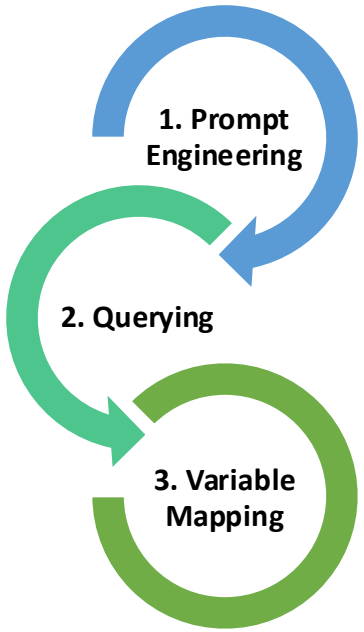
”

Background

Examples

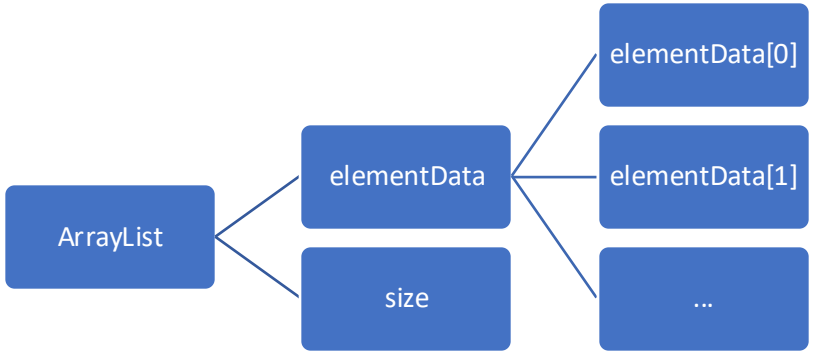
Question

Solution Version 1



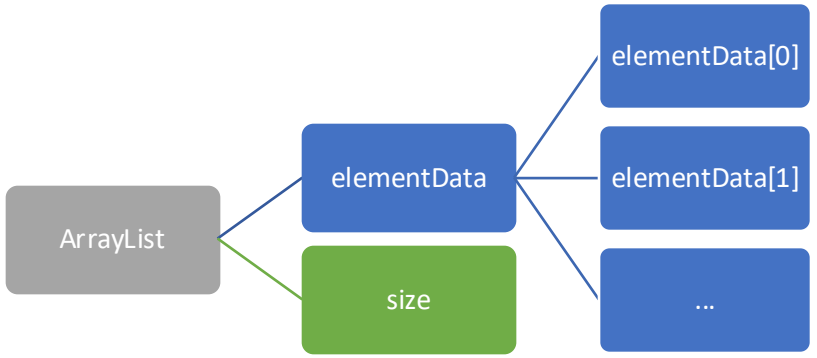
Variable Mapping (V1)

- V1 assumes that each data structure contains:
  - an internal array
  - a field named “size”

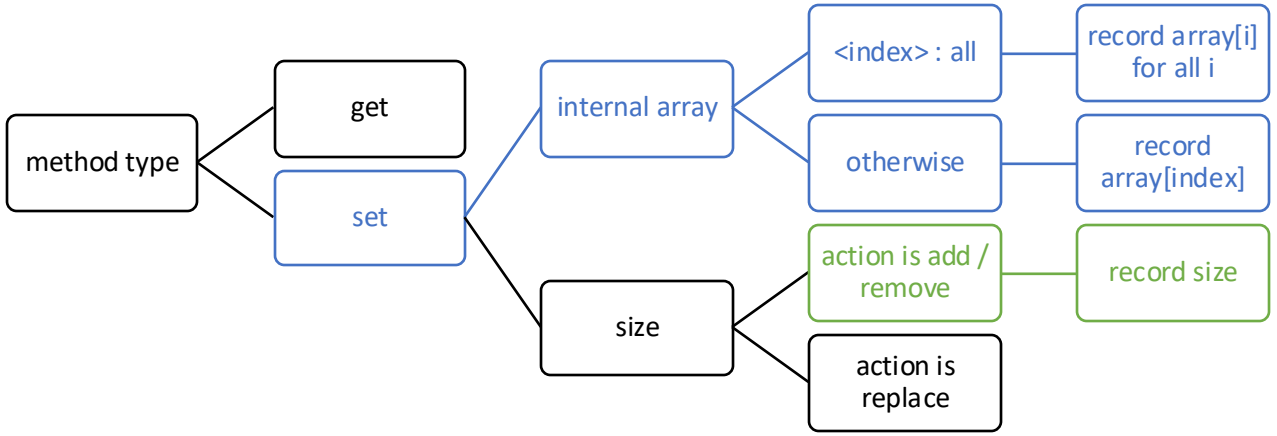


Solution Version 1

Query Response Format:
$< method\ type >< method\ action >< name\ of\ internal\ array >< index >$



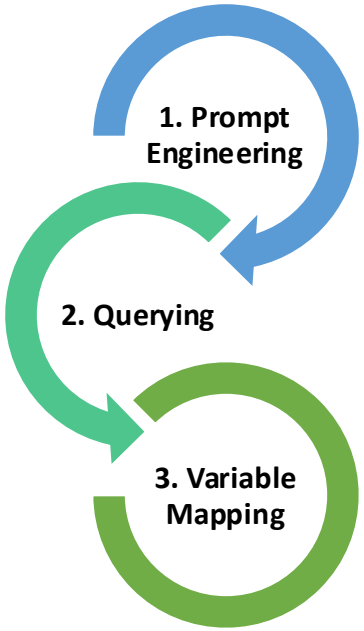
Variable Mapping (V1)



Solution Version 1 Limitations

1. Some data structures do not follow the structure specified in Prompt V1
   - e.g. LinkedList contains Nodes instead of an array
2. Sometimes index cannot be inferred correctly
   - e.g. index in PriorityQueue cannot be inferred
3. Static methods might modify multiple input variables
   - Classifier only works on one variable

Solution Version 2



Prompt Engineering (V2)

- Using LLM as a predictor
- Input: execution information
  - code
  - method signature
  - variable values
- Output: critical variables
- Input Variable Format:
  - {name:var_name, type:var_type, value:var_value}
  - var_value can be further expanded
- Output Variable Format:
  - $< layer\ 1\ var\_name\#layer\ 2\ var\_name\#\ \ldots\#critical\ var\_name >$

Solution Version 2

Prompt Format (V2)

Let {variable format} represent a variable. Return the fields in var_value that are modified. In your response, do not explain and return strictly in this format: <response format>

e.g., Given variable {example variable} After calling {code} once, the following fields of {variable name} are modified:<critical variable 1 name>;<critical variable 2 name>;...

Then given variables {queried variable 1} {queried variable 2} ... After calling {code} once, the following fields of {queried variable 1 name}, {queried variable 2 name}, ... are modified:

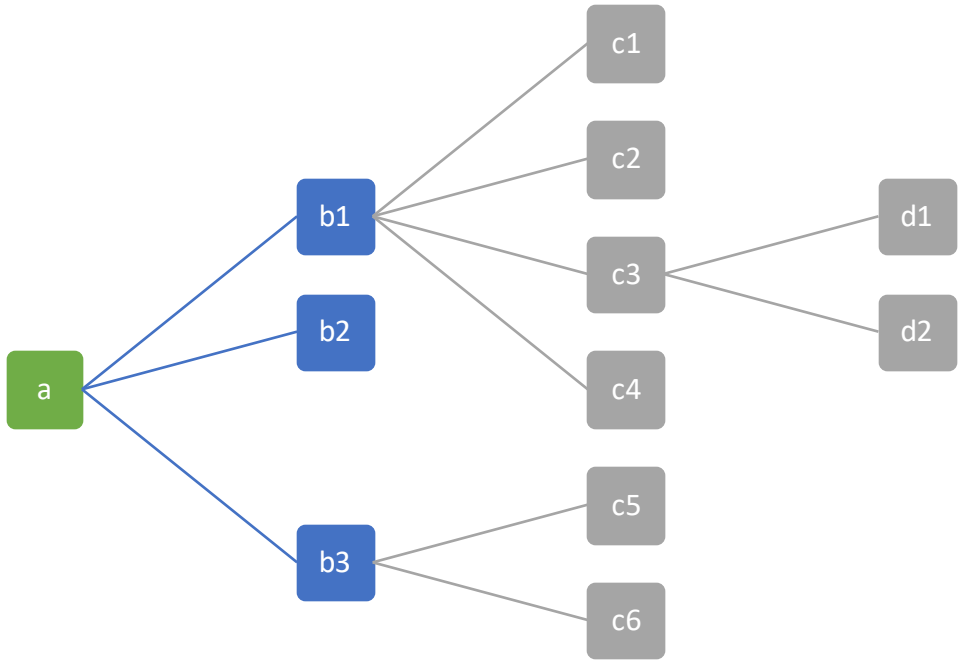
Background

Examples

Question

Solution Version 2

Tree Representation of Variable



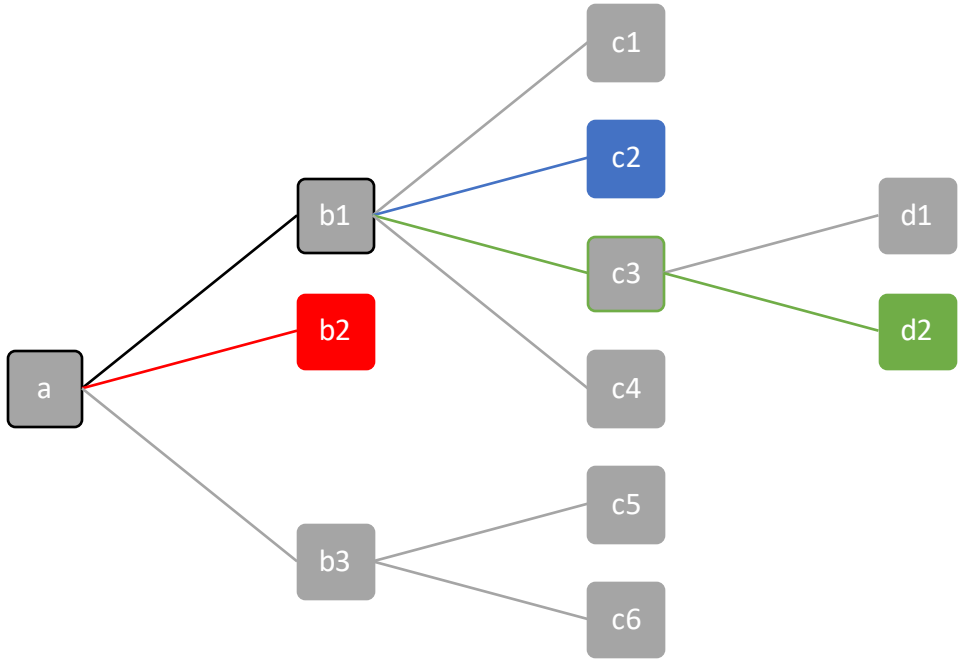
Prompt Engineering (V2)

Query Request Format:

```
{
 name: a, type: a_type, value: [
  {name: b1, type: b1_type, value: b1_value},
  {name: b2, type: b2_type, value: b2_value},
  {name: b3, type: b3_type, value: b3_value}
 ]
}
```

Solution Version 2

Tree Representation of Variable

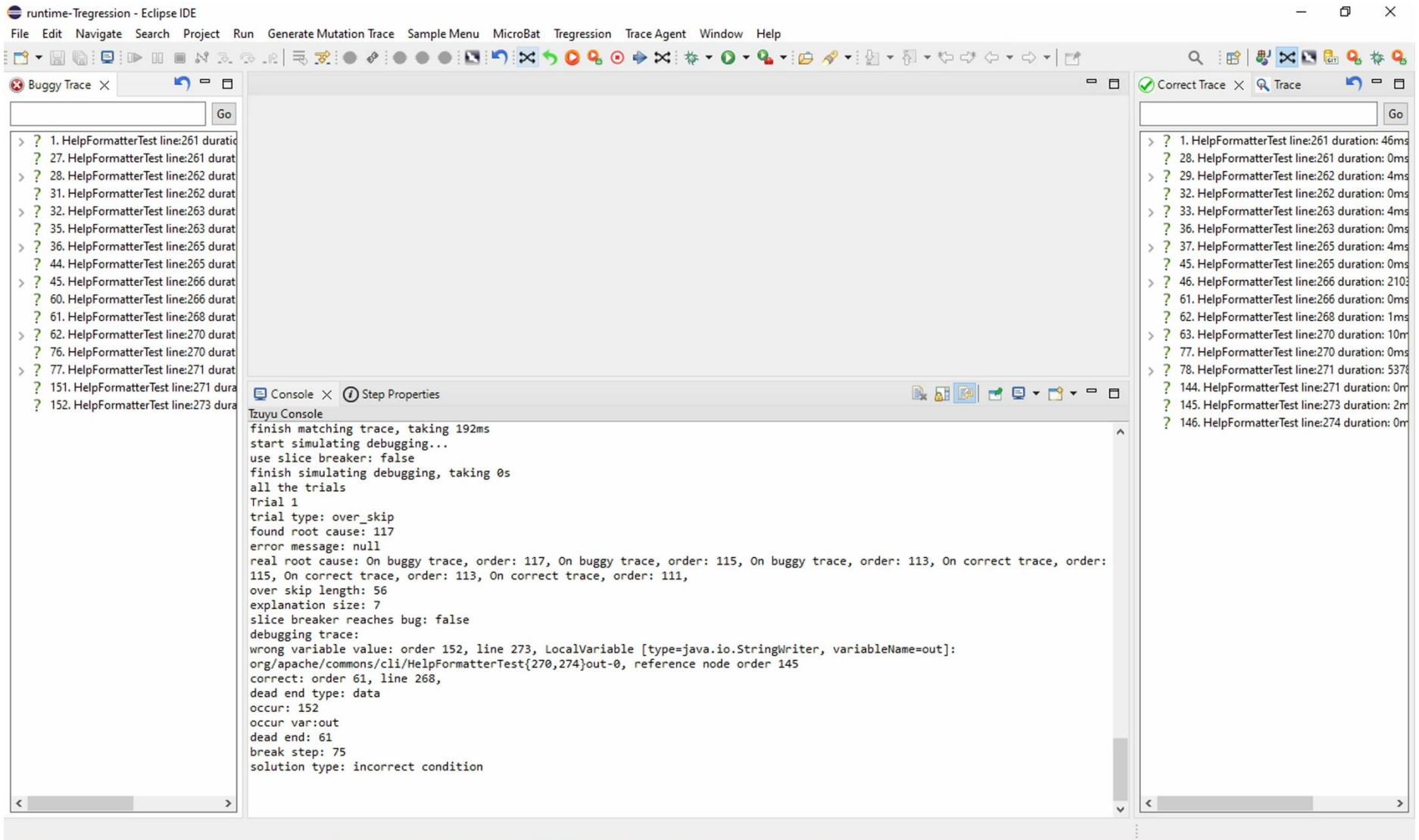


Variable Mapping (V2)

Query Response Format:

$$< a\#b1\#c2 > ; < a\#b1\#c3\#d2 > ; < a\#b2 >$$

Performance on Motivating Example



Evaluation

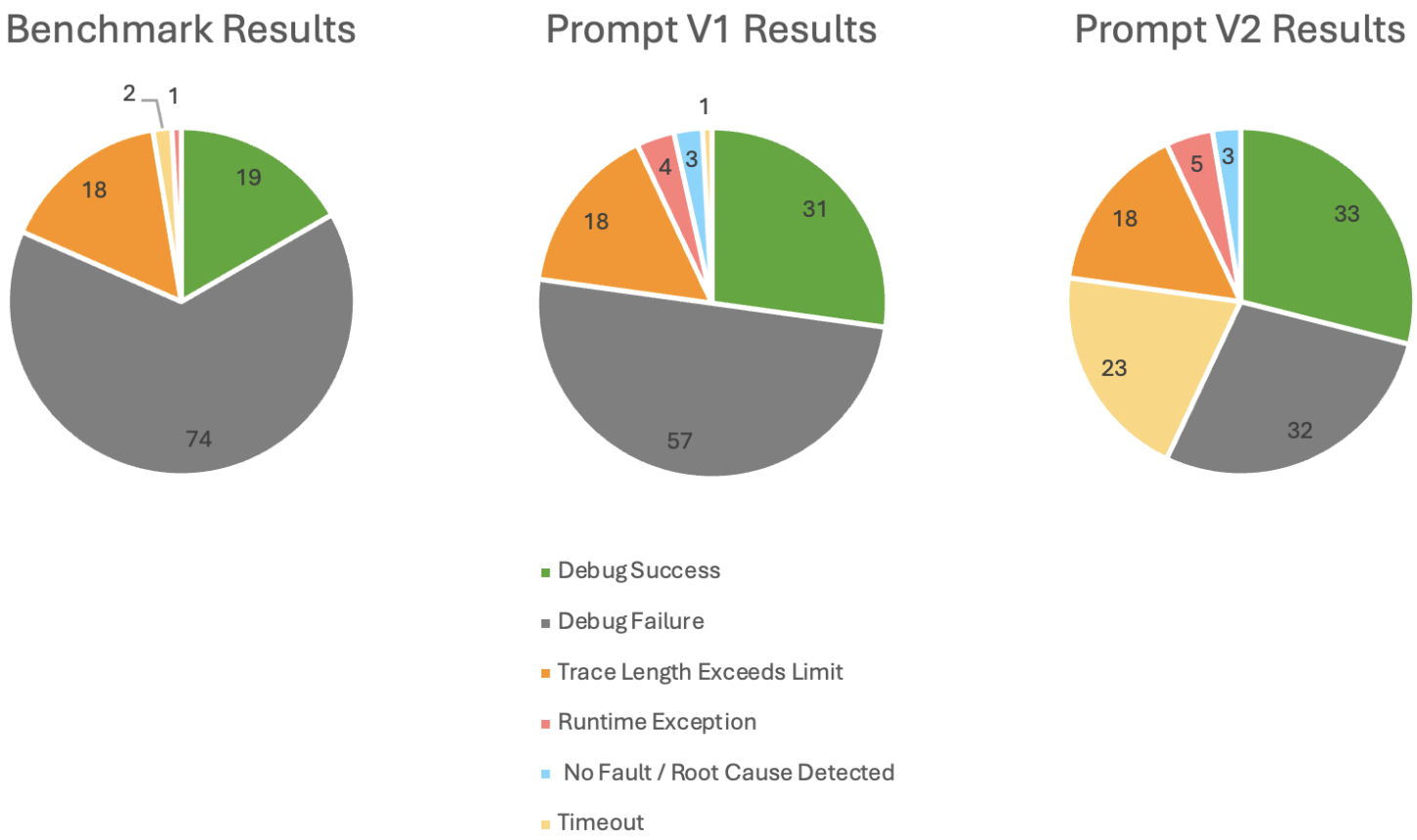
Dataset

- Defects4J
- 841 programs in total
- 114 programs
  - Trace can be generated
  - Microbat cannot locate the root cause

Benchmark

- Hardcoded responses in the format of prompt V1
- 4 representative data structures:
  - ArrayList
  - HashMap
  - HashSet
  - Queue
- 34 setter methods

Performance of Prompt V1 and V2 compared to benchmark



Performance of Prompt V1 and V2 compared to benchmark

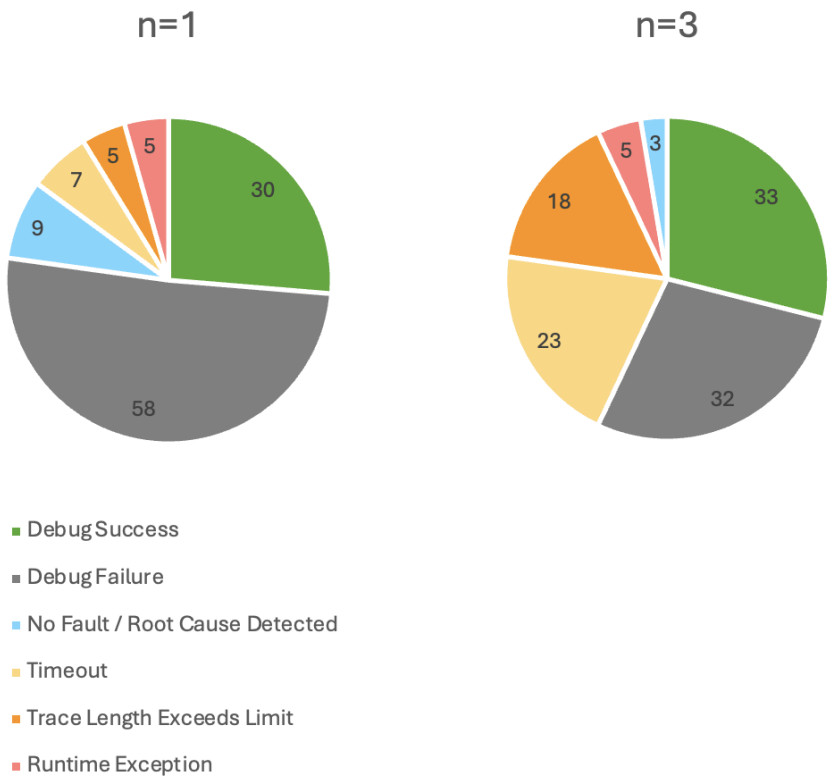
	Debugging Success	Trace Generation Success	Percentage of Success	Average Trace Generation Time (s)
Benchmark	19	93	20.43%	19.00
Prompt V1	31	88	35.23%	29.21
Prompt V2	33	65	50.77%	128.44

Microbat Experiment Result with Data Dependency Recovery

	Debugging Success	Trace Generation Success	Percentage of Success	Average Trace Generation Time (s)
Benchmark	12	65	18.46%	15.65
Prompt V1	22	65	33.85%	15.20
Prompt V2	33	65	50.77%	128.44

Subset of Microbat Experiment Result with Data Dependency Recovery

Performance of Prompt V2 for n=1 and n=3



	Debugging Success	Trace Generation Success	Percentage of Success	Average Trace Generation Time (s)
n=1	30	88	34.09%	117.15
n=3	33	65	50.77%	128.44

Microbat Experiment Result with Data Dependency Recovery V2 (n=1 and n=3)

Conclusions

Limitations and Future Research

Limitation: Runtime Overhead

- Version 2 times out due to the runtime overhead for querying ChatGPT

Future Research Directions

1. Reduce the number of queries
   - On-demand dependency recovery
   - Only send queries when a variable is selected for data slicing
2. Reduce the query time
   - Use a local deep learning model instead of ChatGPT

Limitations and Future Research

Limitation: Recovery Rate

- The debugging success rate is 50.77%

Future Research Directions

1. Include more execution information in the prompt
   - e.g. Context in the form of source code
   - Need to determine the scope of the context

Thank You