

# Tracing Optimization for Performance Modelling and Regression Detection

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01

# The Problem

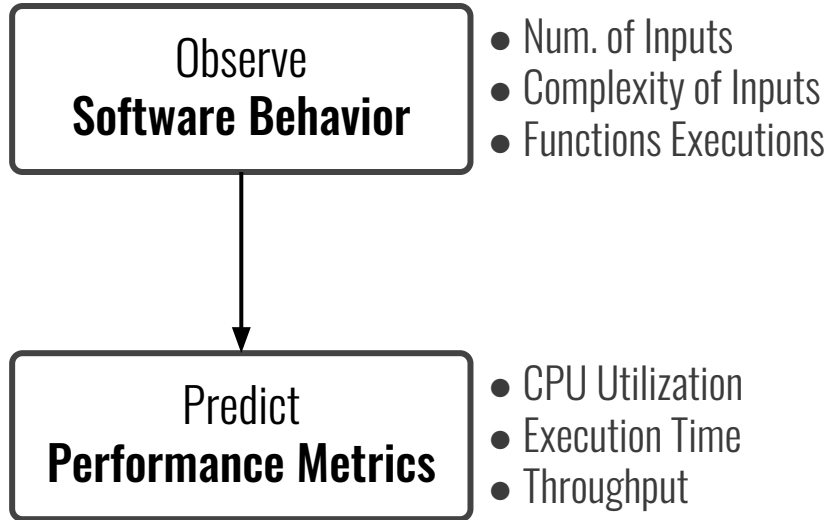
# What is Performance Modelling?



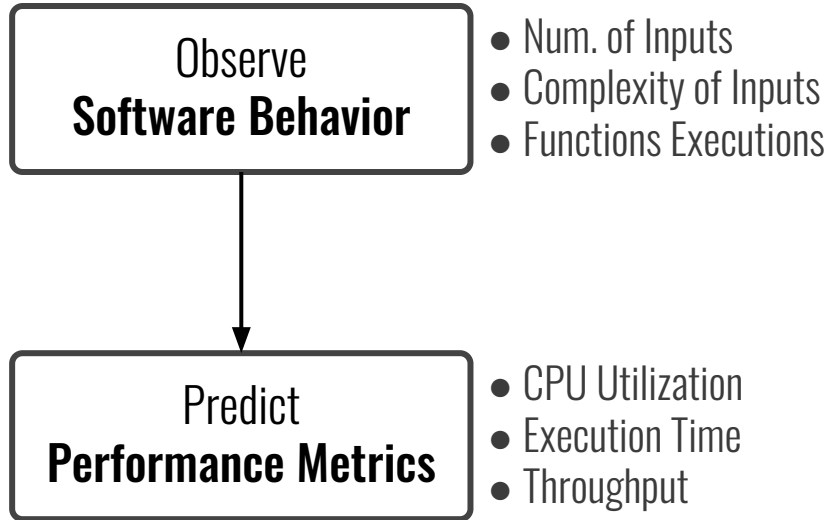
Observe  
**Software Behavior**

- Num. of Inputs
- Complexity of Inputs
- Functions Executions

# What is Performance Modelling?



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## Performance Regression?

The performance model **MUST** be able to **DETECT** the performance **regressions**

# What is Performance Modelling?

In this study, the **performance model** is a **regression model**, **functions tracing data** are the **inputs**, and the **program's execution time** is the **output**.

Predict  
Performance Metrics

- CPU Utilization
- Execution Time
- Throughput

# The Trade-Off

**A: GOOD**

## Performance Model Precision

Using **functions tracing**, the **accuracy** of the **performance model** is **great!**

```
● ● ● Performance Model
R2 Score: > 99%
Mean Error: < 5%
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BUT

## B: BAD

### The Overhead of Tracing

The **added overhead** to the **system** regarding the **execution time** and **storage usage** is **massive!**

```
● ● ● Resources
Mean Time Overhead: > 55%
Mean Storage Overhead: >> 1000%
```



But, with respect to performance modelling, not all of the functions have significant impact on the model and can be removed from tracing

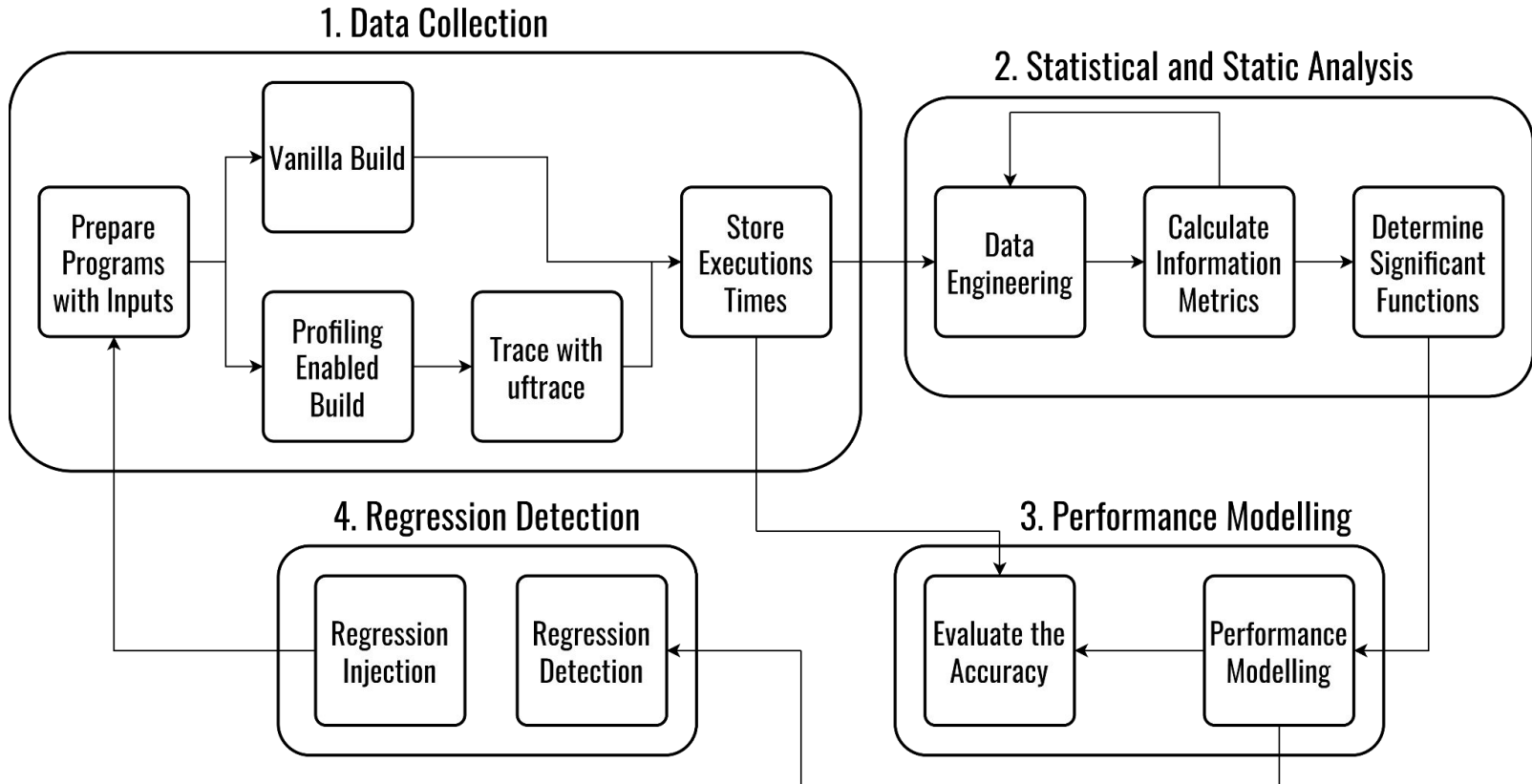


# 02

## The Methodology



# Overall Steps



# 1. Data Collection

## I. Programs (Benchmarks)

- A. SPEC CPU 2017: 631.deepsjeng\_s (Int), 638.imagick\_s (FP)
- B. SPEC MPI 2007: 104.milc
- C. SU2
- D. PARSEC: freqmine

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II. **Input Generation** -> More than 10k combinations of inputs

III. **Run the Programs in Vanilla Mode and Full Tracing, and Store the Execution Times along with Storage Usage**

# 2. Statistical and Static Analysis

## I. Calculating Several Metrics of the Functions' Executions

- A. Entropy, Coefficient of Variant, and Ridge Regression Coefficients
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## III. Extracting Functions Characteristics

- A. Complexity, LoC, Number of loops, Number of calls, etc.
- B. These characteristics will be used for the further steps of this study

# 3. Performance Modelling

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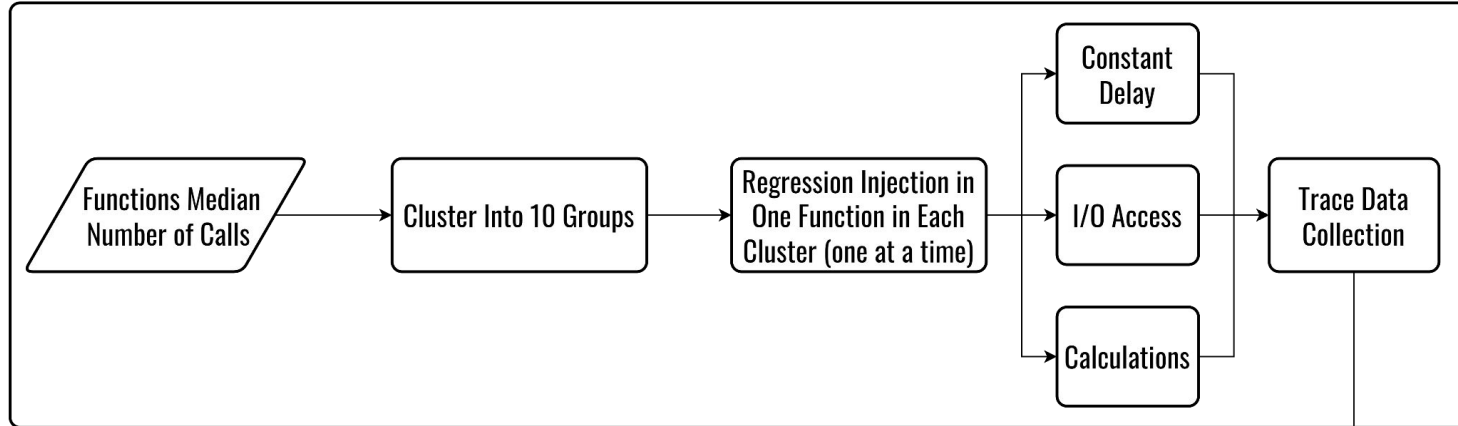
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## III. Evaluating the Optimized Performance Model

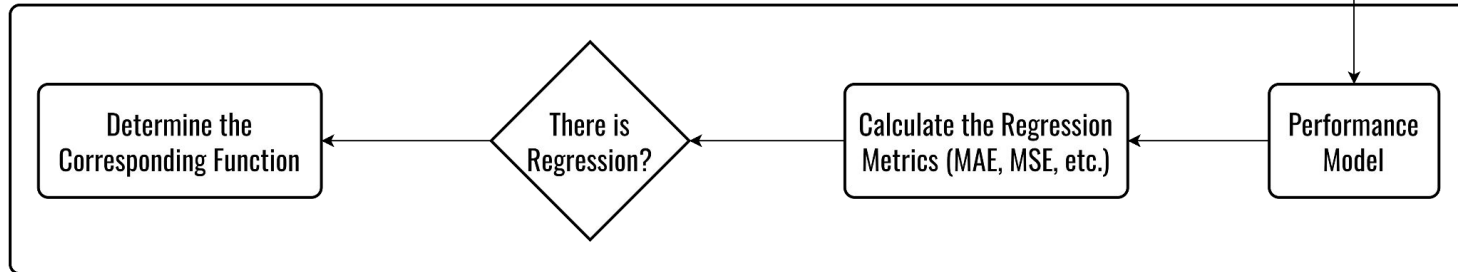
- A. The accuracy of the performance model itself
- B. Performance regression detection

# 4. Regression Detection

## 1. Regression Injection



## 2. Regression Detection



# 03

## The Results



# 1. Data Collection

## Programs Collected Data

- 631.deepsjeng\_s: 9,000 executions
- 638.imagick\_s: 2,350 executions
- 104.milc: 4,650 executions
- SU2: 4,700 executions
- Freqmine: 4,200 executions

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### Times

Total execution times  
of the program  
(vanilla, fully traced)

### Storage Usage

The overhead of used  
storage by tracing

### Parameters

The input parameters  
for that specific  
execution

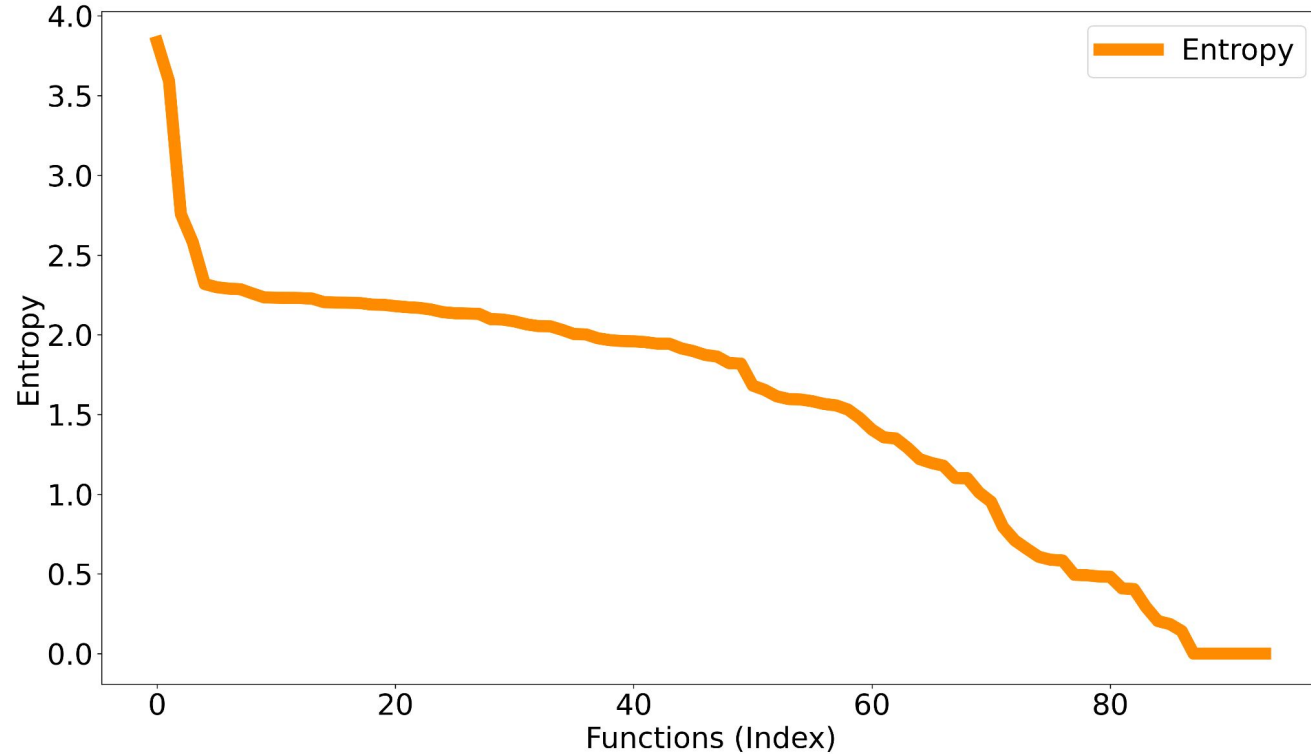
### Functions

Self time, cumulative  
time, number of calls



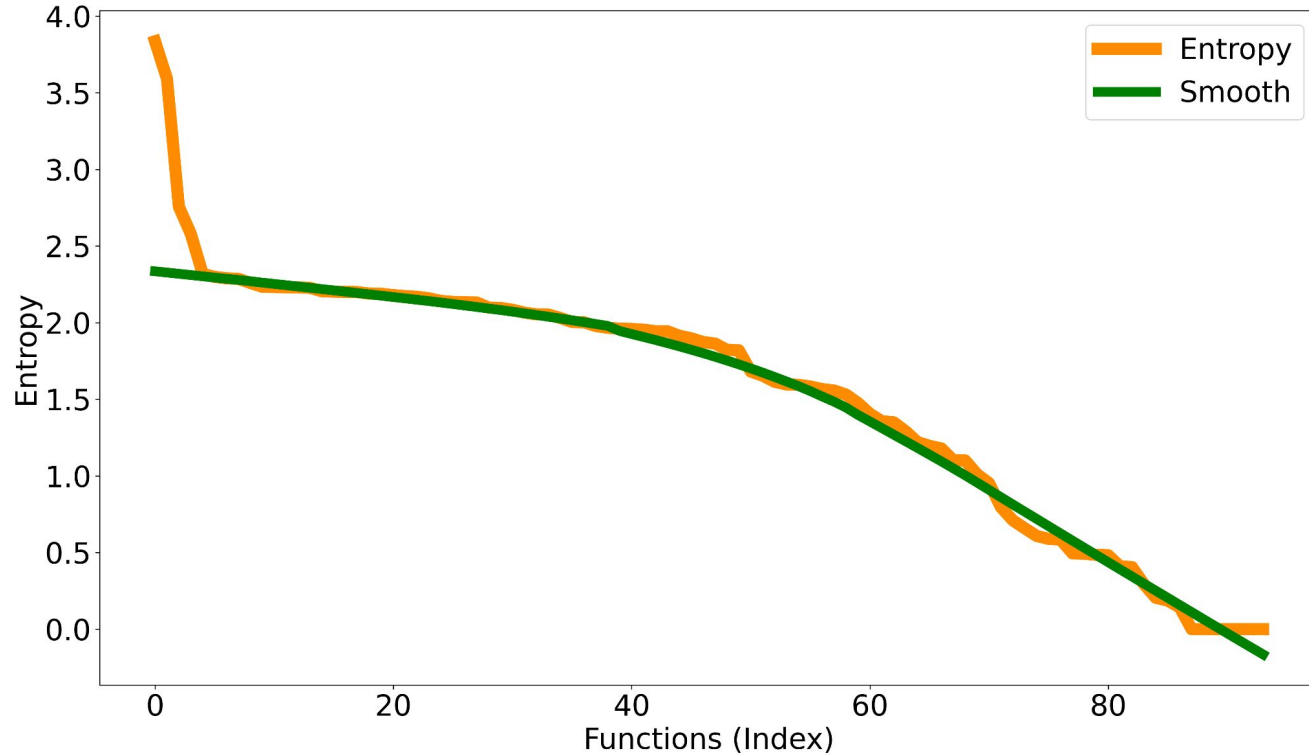
# 2. Statistical and Static Analysis

Program: 631\_sjeng



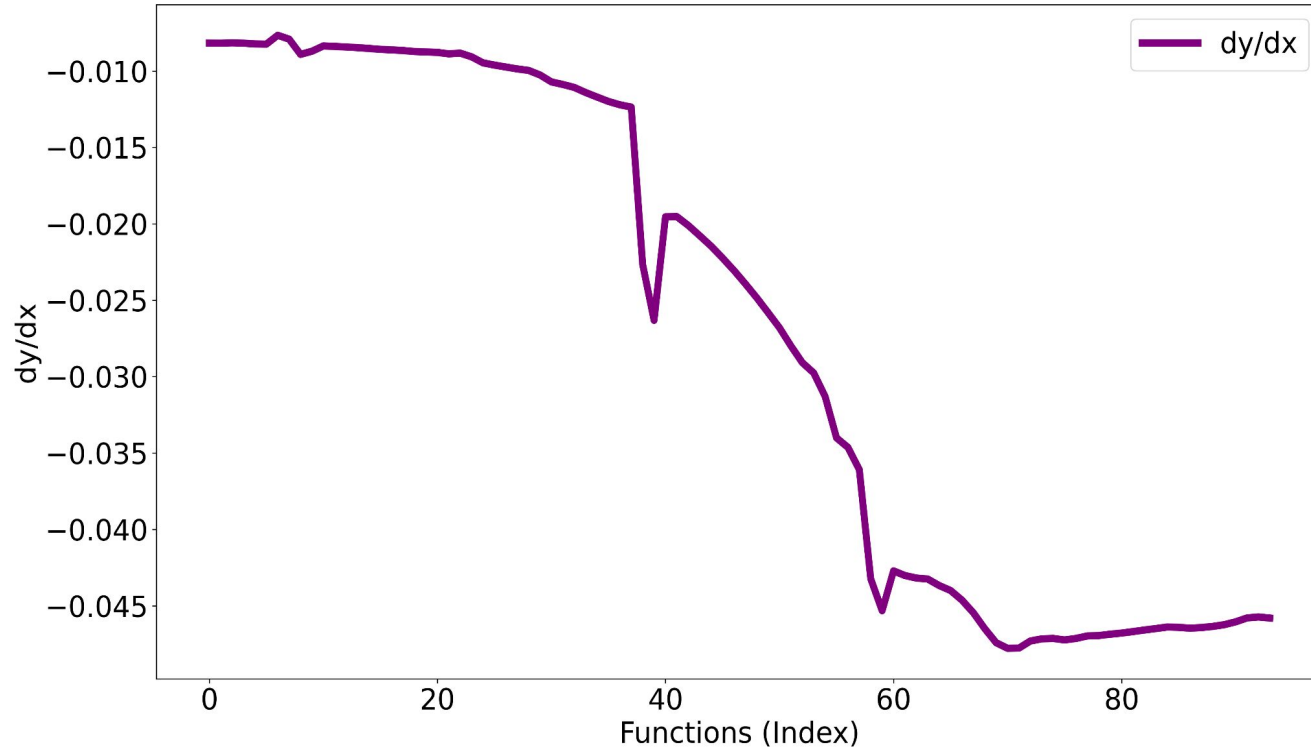
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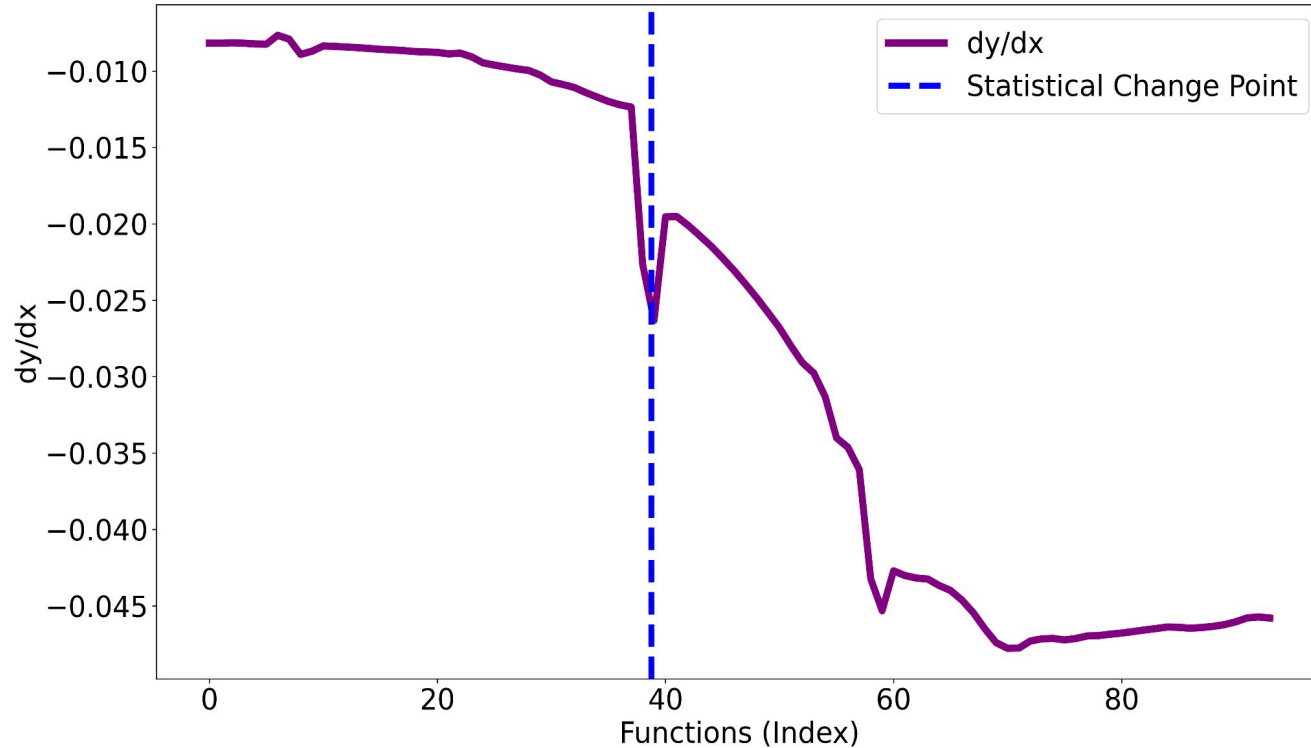
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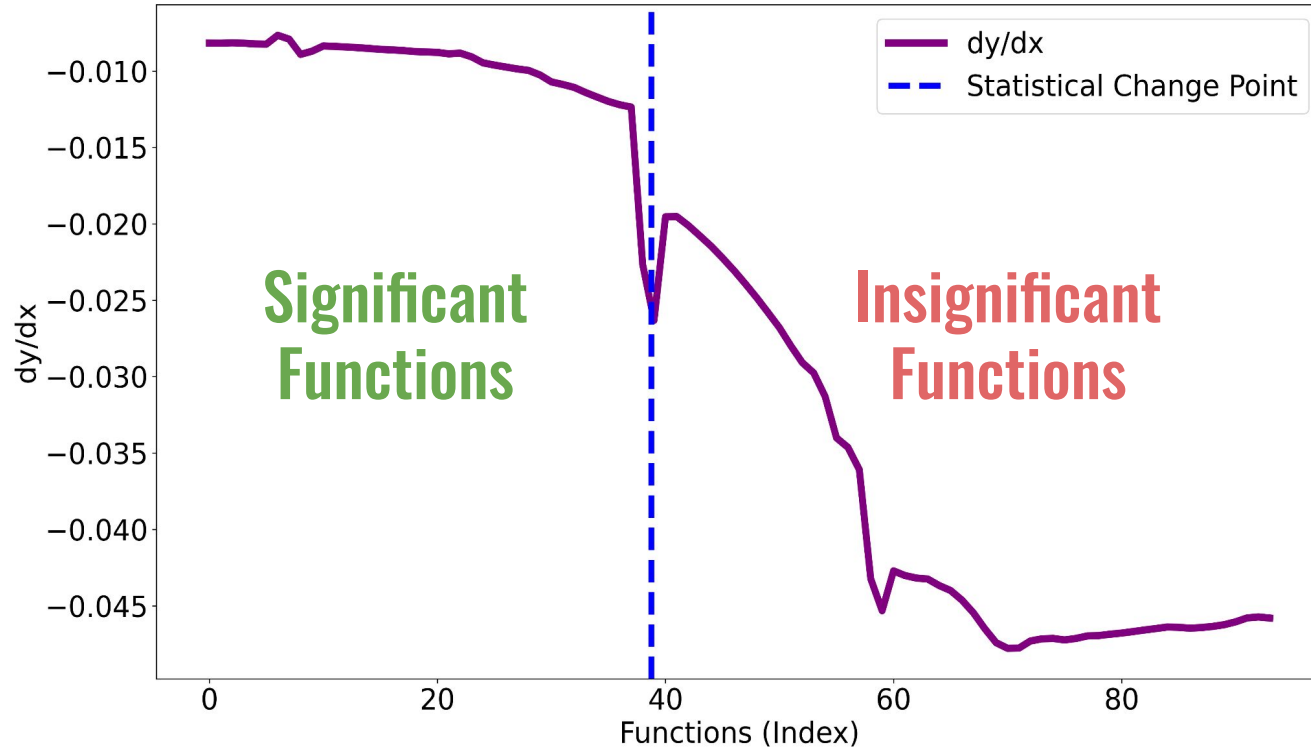
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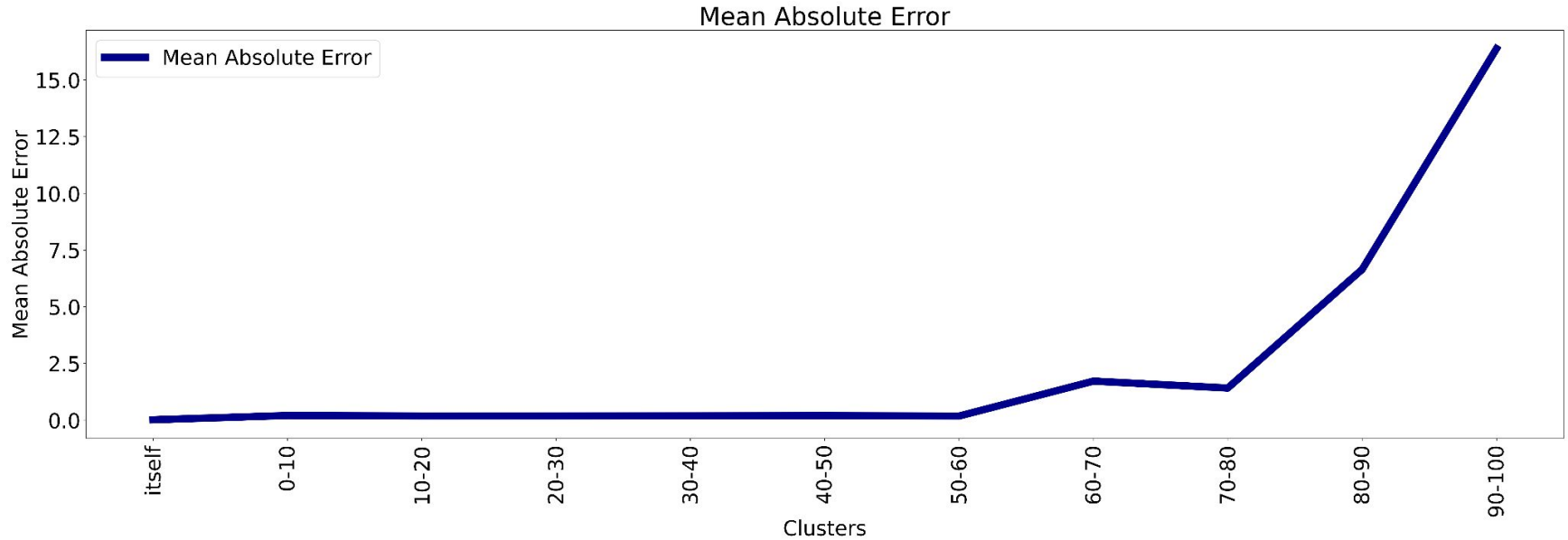


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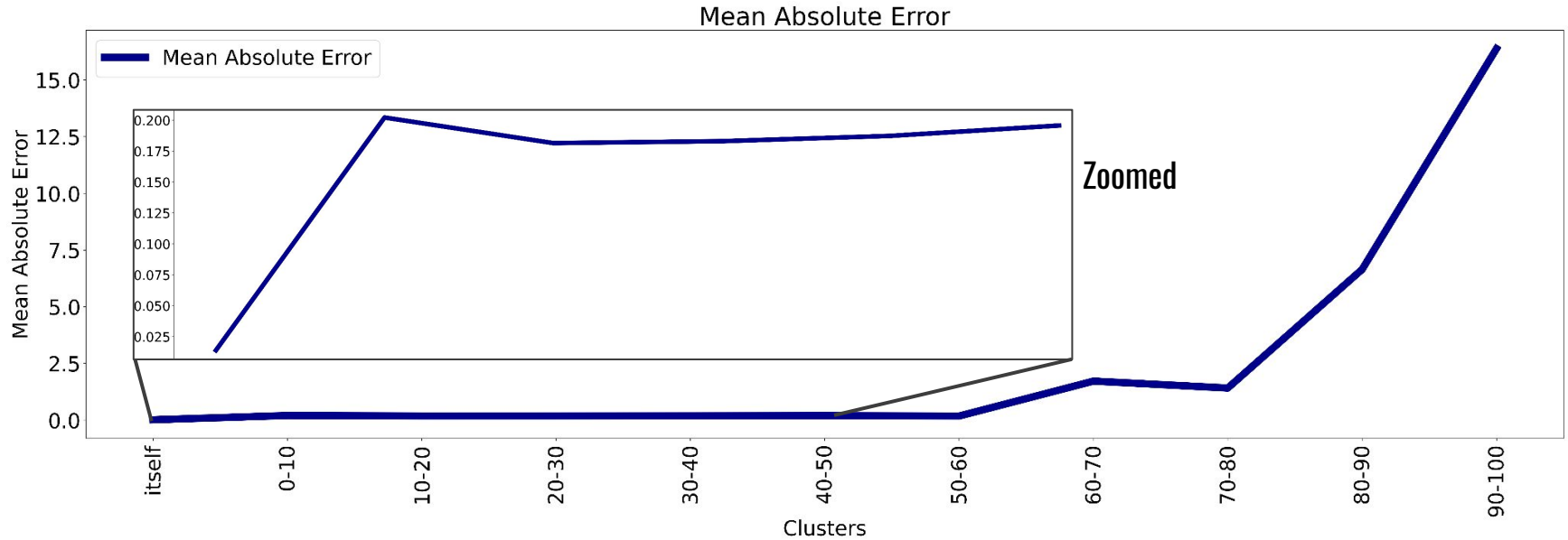
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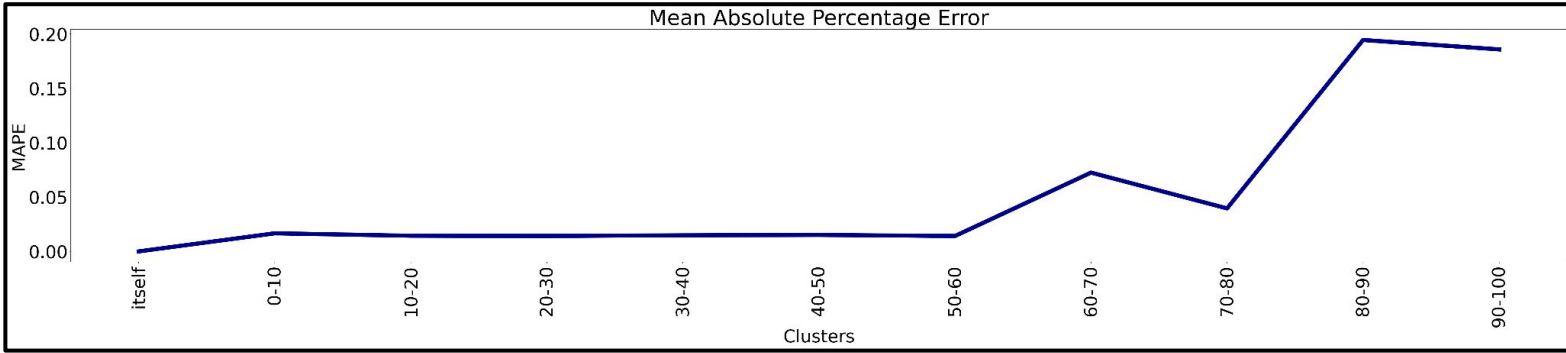
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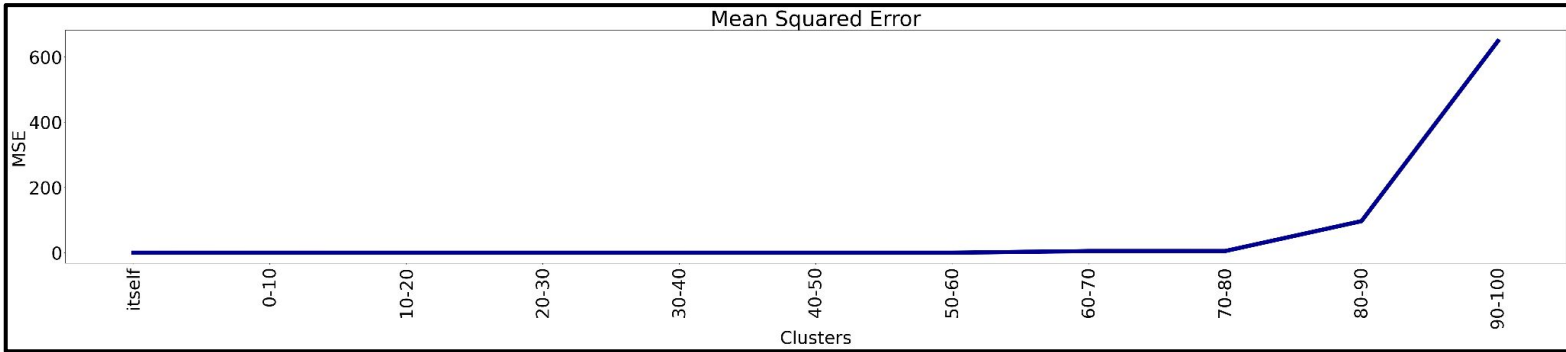
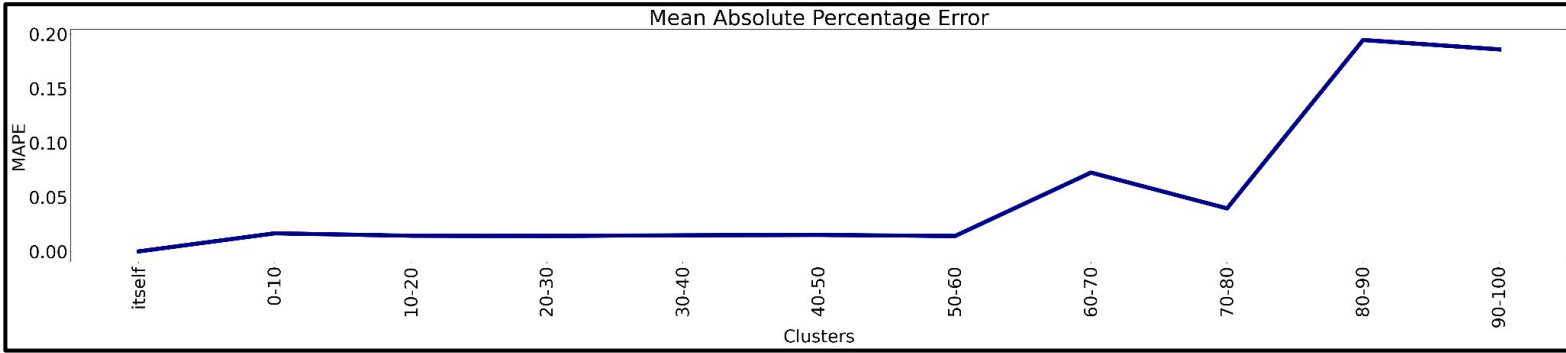


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# 04 The Next Steps



# Next Steps

## I. Regression Detection Analysis

- A. Investigate further the performance model's accuracy
- B. Change the injected regressions types

# Next Steps

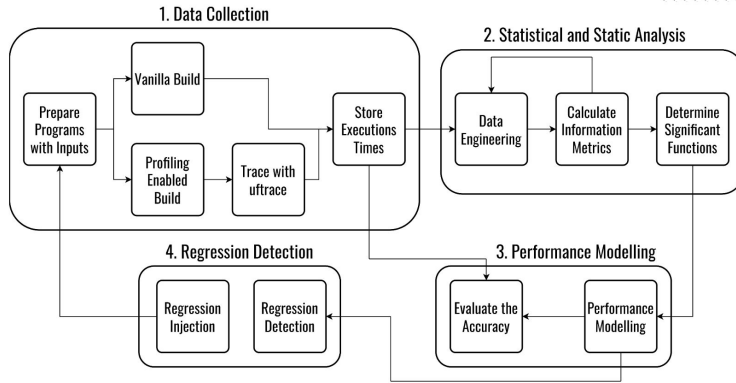
## I. Regression Detection Analysis

- A. Investigate further the performance model's accuracy
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## II. Statistical and Static Analysis of the Characteristics of the Functions

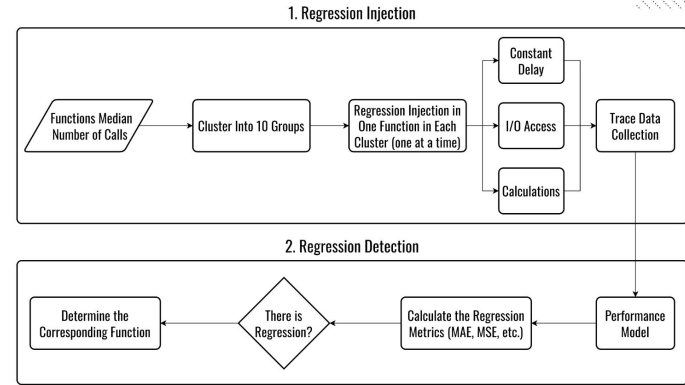
- A. Check whether it is possible (and accurate) to build an optimized performance model just through a statistical analysis of the program's source code
- B. Compare the impact of each function metric (LoC, Loops, etc.) on the performance model's accuracy

# Overall Steps



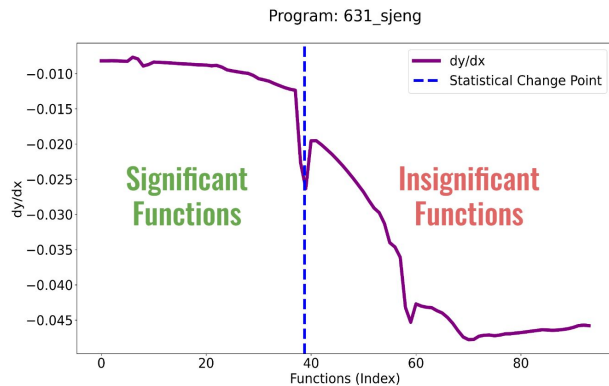
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# 4. Regression Detection



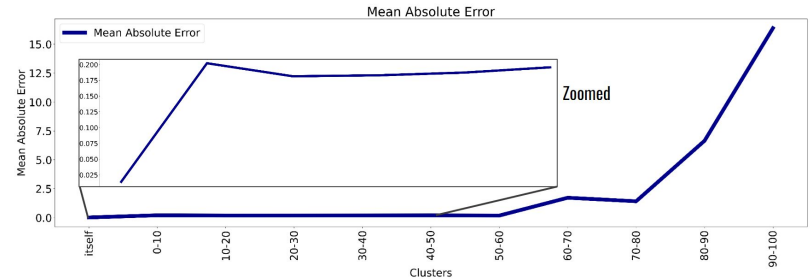
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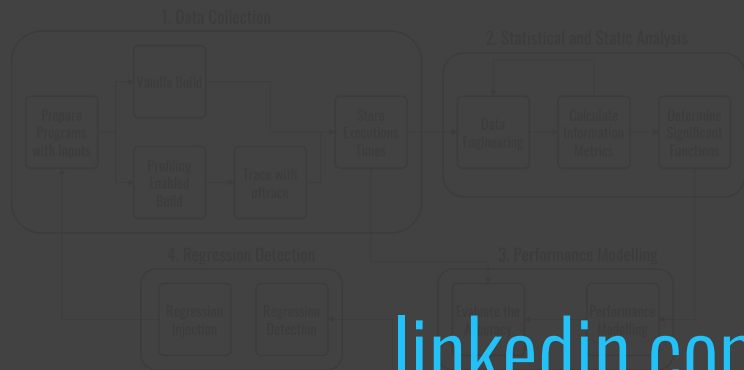
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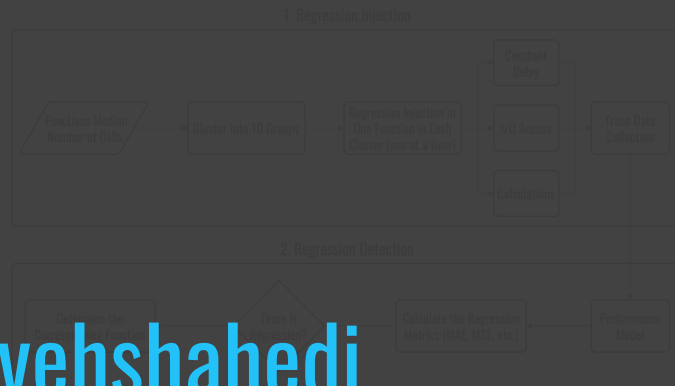


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## Overall Steps



## 4. Regression Detection



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## 2. Statistical and Static Analysis



## 3. Regression Injection and Detection

