Optimizing Symbolic Execution Through Taint Analysis and Path Prioritization

Bachelor thesis

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Abstract

Symbolic execution is a powerful program analysis technique widely used for vulnerability discovery and test case generation. However, its practical application is often hampered by scalability issues, primarily due to the "path explosion problem" where the number of possible execution paths grows exponentially with program complexity. This thesis addresses this fundamental challenge by proposing an optimized approach to symbolic execution that integrates taint analysis and path prioritization.

The core contribution is a novel exploration strategy that moves away from uniform path exploration towards targeted analysis of security-critical program behaviors. The approach prioritizes execution paths originating from memory allocations and user input processing points, as these represent common sources of vulnerabilities. By leveraging dynamic taint analysis, the system identifies and tracks data flow from these critical sources, enabling the symbolic execution engine to focus computational resources on paths influenced by tainted data while deprioritizing paths with no dependency on external inputs.

The implementation integrates this taint-guided exploration strategy with the angr symbolic execution framework, introducing a scoring mechanism that dynamically adjusts path prioritization based on taint propagation. The effectiveness of this optimization is evaluated through comparative analysis, examining runtime efficiency, path coverage quality, and vulnerability discovery capabilities. Results demonstrate that this approach can significantly reduce the search space while maintaining or improving the detection of security-relevant program behaviors, making symbolic execution more practical for large and complex software systems.

Table of Contents

1

Introduction

Challenges in Program Analysis. Symbolic execution is a powerful program analysis technique used for vulnerability discovery, test case generation, and software property verification.

Beyond security analysis, symbolic execution serves as a foundation for various software verification tasks, including bug detection, correctness checking, and automated program reasoning.

However, in large software systems, often lacking a well-defined analysis entry point, finding suitable starting points for symbolic execution is far from straightforward. Programs frequently serve a wide range of use cases, contain numerous execution paths, and can be expansive enough to obscure which code regions are security-critical and drive the core vulnerability landscape.

Moreover, symbolic execution faces a fundamental scalability challenge known as the "path explosion problem". As program complexity increases, the number of possible execution paths grows exponentially, quickly overwhelming computational resources and rendering the analysis intractable for real-world software systems. One recent example demonstrating this challenge is the analysis of complex libraries like OpenSSL, where millions of execution paths can emerge from relatively small input variations, making exhaustive analysis computationally prohibitive.

Despite the importance of efficient symbolic execution, practitioners lack an automated method to intelligently prioritize promising execution paths for security analysis. Manually determining where analysis should begin can be tedious and error-prone. The structure of even medium-sized programs can be extremely cluttered and overwhelming. Current symbolic execution engines typically employ uniform exploration strategies, treating all program paths with equal priority regardless of their potential security relevance, as Figure 1.1 illustrates with a simplified program control flow.

Addressing this issue could significantly enhance both the efficiency and thoroughness of symbolic execution for security testing.

Taint Analysis Motivation: Traditional symbolic execution treats all execution paths with equal priority, failing to distinguish between security-critical paths that process user input and auxiliary paths that handle internal program state. This uniform treatment leads

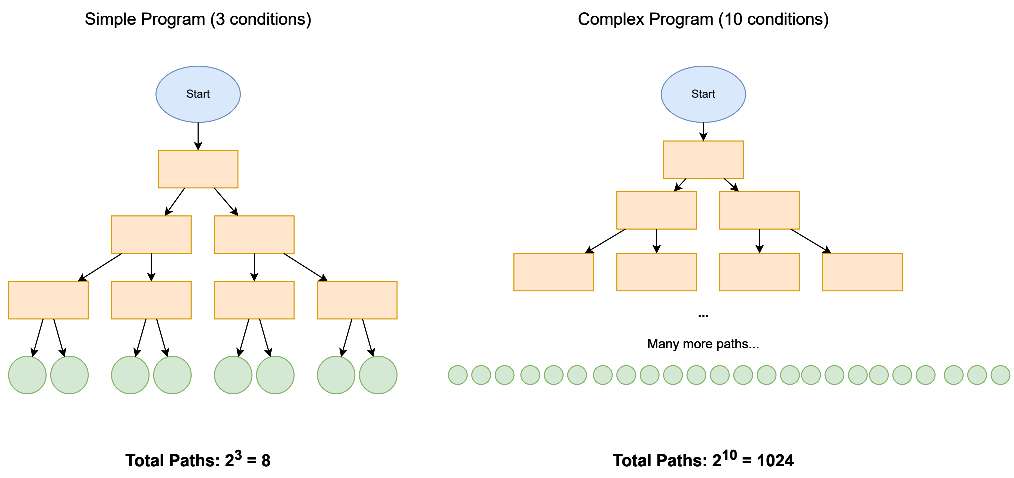

Figure 1.1: Illustration of the path explosion problem: As program complexity increases from 3 to 10 conditions, the number of possible execution paths grows exponentially from 8 to 1024 paths.

to computational waste on paths unlikely to contain vulnerabilities.

Thesis Overview. This work presents TraceGuard[1], a novel approach that integrates taint analysis with symbolic execution to enable intelligent path prioritization. The methodology identifies and tracks data flow from critical sources such as user inputs and memory allocation sites, guiding the symbolic execution engine to focus computational resources on paths most likely to exhibit security-relevant behaviors. The main contributions of this thesis are:

- **Taint-Guided Path Prioritization:** A novel integration of dynamic taint analysis with symbolic execution that uses taint propagation patterns to intelligently prioritize exploration of security-relevant execution paths.
- **Adaptive Scoring Algorithm:** A scoring mechanism that dynamically adjusts path priorities based on real-time taint analysis results, enabling the symbolic execution engine to focus computational resources on the most promising program regions.
- **Practical Implementation:** A complete implementation of the proposed approach using the angr symbolic execution framework, demonstrating the feasibility and effectiveness of taint-guided exploration in a production-quality tool.
- **Empirical Evaluation:** Comprehensive evaluation comparing the proposed approach against standard symbolic execution techniques, which will measure improvements in analysis efficiency, vulnerability discovery rate, and overall scalability.

The effectiveness of this optimization will be evaluated through extensive experimentation on representative programs, examining key metrics including runtime efficiency, path coverage quality, and vulnerability detection capabilities. Preliminary analysis indicates that the taint-guided approach can significantly reduce analysis time while maintaining or

[1] https://github.com/ruben-hutter/TraceGuard

improving the detection of security-relevant program behaviors, making symbolic execution more practical for analyzing large and complex software systems.

The thesis is organized as follows:

- **Chapter 2** reviews essential background concepts including symbolic execution, taint analysis, and the angr framework.
- **Chapter 3** presents the conceptual framework and theoretical algorithms underlying the taint-guided exploration strategy.
- **Chapter 4** details the practical implementation of the proposed approach, including integration with angr and the design of the scoring mechanism.
- **Chapter 5** presents a comprehensive evaluation of the approach, comparing its performance against standard symbolic execution techniques.
- **Chapter 6** discusses related work in symbolic execution optimization and path prioritization.
- **Chapter 7** concludes with a summary of contributions and implications for future research.
- **Chapter 8** explores potential extensions and future research directions.

2 Background

This chapter establishes the theoretical foundations necessary for understanding the optimization techniques presented in this thesis. We examine symbolic execution, taint analysis, program analysis techniques, and the Angr framework.

2.1 Symbolic Execution

Symbolic execution is a static analysis technique that explores program execution paths by using symbolic variables instead of concrete inputs. The program state consists of symbolic variables, path constraints, and a program counter. When execution encounters a conditional branch, the engine explores both branches by adding appropriate constraints to the path condition.

A fundamental challenge in symbolic execution is the path explosion problem. As program complexity increases, the number of possible execution paths grows exponentially, making exhaustive exploration computationally intractable. This scalability issue particularly affects real-world applications with complex control flow structures and deep function call hierarchies. Research has shown that symbolic execution tools designed to optimize statement coverage often fail to cover potentially vulnerable code due to complex system interactions and scalability issues of constraint solvers [7].

Various techniques address the scalability challenge, including state merging [4], constraint optimization, and compositional analysis methods. Recent advances include veritesting approaches that combine dynamic and static symbolic execution [2] and compilation-based symbolic execution achieving orders of magnitude performance improvements [6]. Path prioritization strategies represent another important direction, with modern approaches including coverage-guided exploration, target-directed search, and machine learning-based path selection [3][2].

Traditional symbolic execution typically employs a forward approach, starting from the program's entry point and exploring paths toward potential targets. However, this method may struggle to reach deeply nested functions or specific program locations of interest.

[2] https://github.com/ksluckow/awesome-symbolic-execution

Backward symbolic execution, conversely, begins from target locations and works backwards to identify input conditions that can reach those targets. Compositional approaches combine both techniques by analyzing individual functions in isolation and then reasoning about their interactions.

2.2 Taint Analysis

Taint analysis tracks the propagation of data derived from untrusted sources throughout program execution. Data originating from designated sources (such as user input functions like `fgets`, `gets`, `read`, or `scanf`) is marked as "tainted." The analysis tracks how this tainted data flows through assignments, function calls, and other operations. When tainted data reaches a security-sensitive sink (such as buffer operations or system calls), the analysis flags a potential vulnerability.

The propagation rules define how taint spreads through different operations: assignments involving tainted values result in tainted variables, arithmetic operations with tainted operands typically produce tainted results, and function calls with tainted arguments may result in tainted return values depending on the function's semantics. Dynamic taint analysis performs tracking during program execution, providing precise information about actual data flows while considering specific calling contexts and program states, resulting in reduced false positives compared to static analysis approaches.

The combination of taint analysis and symbolic execution creates a powerful analysis framework. Symbolic execution can explore multiple program paths while taint analysis identifies which paths involve security-relevant data flows. Research has demonstrated effective integration through pipelined approaches that achieve significant performance improvements while maintaining precision [5]. This integration enables targeted exploration of paths that process untrusted input, significantly improving the efficiency of vulnerability discovery[3].

2.3 Program Analysis Techniques

Static analysis inspects program code without executing it, analyzing structure, data flow, and control flow based solely on the source code or binary representation. This approach offers comprehensive coverage and efficiency, enabling examination of all program paths without requiring specific input values. However, static analysis faces limitations including difficulty with indirect call resolution and potential false positives due to conservative approximations required for soundness.

Dynamic analysis executes the program and collects runtime information, providing precise information about actual program behavior and complete execution context. This approach eliminates many false positives inherent in static analysis and validates that potential issues are actually exploitable under realistic conditions. However, dynamic analysis results depend heavily on input quality and coverage, and achieving exhaustive coverage can

[3] https://github.com/badnack/angr_taint_engine

require exponential time for complex programs.

Modern tools often combine both approaches. Symbolic execution represents a hybrid technique, combining static analysis of program structure with dynamic-style exploration of execution paths. Hybrid approaches have proven particularly effective, such as combining fuzzing with selective symbolic execution for comprehensive vulnerability discovery [10].

A Call Graph (CG) represents function call relationships within a program, where each node corresponds to a function and each directed edge represents a call relationship. Call graphs serve important purposes including program understanding, entry point identification, reachability analysis, and complexity assessment. Call graphs prove valuable for path prioritization strategies, enabling identification of functions reachable from tainted input sources and assessment of their relative importance in program execution flow[4].

2.4 Angr Framework

Angr is an open-source binary analysis platform providing comprehensive capabilities for static and dynamic program analysis [8]. The platform supports multiple architectures and provides a Python-based interface for research and education [9]. Key components include[5]: the Project object representing the binary under analysis with access to contents, symbols, and analysis capabilities; the Knowledge Base storing information gathered during analysis including function definitions and control flow graphs; the Simulation Manager handling multiple program states during symbolic execution and managing state transitions; and the Solver Engine interfacing with constraint solvers to determine path feasibility and solve for concrete input values.

Angr supports both static (`CFGFast`) and dynamic (`CFGEmulated`) CFG construction [1]. Static analysis provides efficiency but may miss indirect calls, while dynamic analysis offers completeness at higher computational cost[6]. The static approach analyzes the binary without execution, making it efficient for initial program understanding, while dynamic analysis executes the program with sample inputs to discover reachable code, providing more complete coverage of actual execution paths and better handling of indirect calls.

Angr represents program states with register values, memory contents, path constraints, and execution history. The framework provides APIs for state inspection and manipulation, along with fine-grained execution control through step functions and exploration techniques[7]. The step function advances execution by single instructions, enabling precise control over exploration processes, while various exploration strategies guide path selection including depth-first search, breadth-first search, and custom heuristics. Configuration options control execution behavior, such as handling of unconstrained memory and registers, allowing researchers to customize analysis behavior for specific research requirements.

The next chapter will present the conceptual framework for integrating these approaches into TraceGuard's optimized symbolic execution strategy.

[4] https://docs.angr.io/en/latest/built-in-analyses/#call-graph
[5] https://docs.angr.io/en/latest/core-concepts/
[6] https://docs.angr.io/en/latest/built-in-analyses/
[7] https://docs.angr.io/en/latest/core-concepts/states/

2.5 Dynamic Taint Analysis

2.6 Taint Sources and Sinks in Security Analysis

2.7 Symbolic Execution State Management

3

Related Work

4

Taint-Guided Exploration

Having established the need for more efficient symbolic execution in Chapter 1, we now turn to the theoretical foundation of TraceGuard's solution. The key insight driving this approach is that not all execution paths are equally valuable for security analysis—paths that interact with user-controlled data are significantly more likely to harbor vulnerabilities than those processing only internal program state.

TraceGuard operationalizes this insight through a dynamic taint scoring mechanism that quantifies the security relevance of each symbolic execution state. The following sections present the conceptual algorithms and design decisions that enable this taint-guided exploration strategy.

4.1 Theoretical Foundation

Traditional symbolic execution engines suffer from the path explosion problem, where the number of possible execution paths grows exponentially with program complexity. TraceGuard addresses this fundamental challenge by introducing a taint-guided exploration strategy that prioritizes paths based on their interaction with user-controlled data.

The central concept revolves around calculating a dynamic "taint score" for each symbolic execution state. This score quantifies how closely a given execution path interacts with tainted data originating from external inputs. By prioritizing states with higher taint scores, the symbolic execution engine directs its computational resources toward program regions that are most likely to contain security vulnerabilities.

The taint score serves as a heuristic measure of security relevance. States that process user inputs, manipulate tainted data, or reach security-critical functions receive higher scores, while states that operate on untainted data or perform auxiliary computations receive lower scores. This approach fundamentally transforms symbolic execution from an exhaustive search into a guided exploration strategy.

4.2 Taint Source Identification

The foundation of TraceGuard's approach lies in accurately identifying taint sources within the analyzed program. Taint sources represent points where external, potentially malicious data enters the program execution flow. These sources serve as the starting points for taint propagation analysis.

Algorithm 1 Taint Source Identification

Require: Program control flow graph CFG, Function set F
Ensure: Set of identified taint sources T

```
T ← ∅
InputFunctions ← {fgets, scanf, getchar, read, recv, ...}
MemoryFunctions ← {malloc, calloc, realloc, ...}
for all function f ∈ F do
    if f.name ∈ InputFunctions then
        T ← T ∪ {f}
        MarkAsTaintSource(f, INPUT)
    else if f.name ∈ MemoryFunctions then
        T ← T ∪ {f}
        MarkAsTaintSource(f, MEMORY)
    end if
end for
for all system call syscall in CFG do
    if IsIOSystemCall(syscall) then
        T ← T ∪ {syscall}
        MarkAsTaintSource(syscall, SYSCALL)
    end if
end for
return T
```

TraceGuard identifies taint sources through static analysis of the program's control flow graph and function call relationships. The system recognizes several categories of taint sources:

Input Functions: Functions that read data from external sources, including standard input/output operations, file operations, and network communications. These functions represent direct pathways for attacker-controlled data to enter the program.

Memory Allocation Functions: Dynamic memory allocation operations are treated as potential taint sources because they create memory regions that may subsequently store user-controlled data. While not inherently tainted, these allocations become relevant when combined with input operations.

System Call Interfaces: Low-level system calls that interact with the operating system kernel, particularly those involved in inter-process communication, file system operations, and network communications.

4.3 Taint Propagation and Tracking

Once taint sources are identified and initial data is marked as tainted, TraceGuard employs a sophisticated taint propagation mechanism to track how tainted data flows through the program's execution. This process involves monitoring data transfers, function calls, and memory operations to maintain accurate taint information.

Algorithm 2 Taint Propagation Analysis

Require: Symbolic execution state s, Operation op, Operands $\{op_1, op_2, ..., op_n\}$
Ensure: Updated taint information

```
tainted ← FALSE
for all operand op_i in operands do
    if IsTainted(s, op_i) then
        tainted ← TRUE
        break
    end if
end for
if tainted then
    result ← ExecuteOperation(op, operands)
    MarkAsTainted(s, result)
    UpdateTaintScore(s, TAINT_INTERACTION)
else
    result ← ExecuteOperation(op, operands)
end if
return result
```

Algorithm 3 Function Call Taint Tracking

Require: Function call f, Parameters $\{p_1, p_2, ..., p_k\}$, State s
Ensure: Updated function taint status and score

```
hasTaintedParams ← FALSE
taintedParamCount ← 0
for all parameter p_i in parameters do
    if IsTainted(s, p_i) then
        hasTaintedParams ← TRUE
        taintedParamCount ← taintedParamCount + 1
    end if
end for
if hasTaintedParams then
    MarkFunctionAsTainted(f)
    if f ∈ InputFunctions then
        UpdateTaintScore(s, INPUT_FUNCTION_BONUS)
    else
        UpdateTaintScore(s, TAINTED_CALL_BONUS)
    end if
    PropagateToReturnValue(s, f)
else
    UpdateTaintScore(s, FUNCTION_CALL_PROGRESS)
end if
```

Data Flow Tracking: TraceGuard tracks taint propagation through register transfers, memory operations, and arithmetic computations. When tainted data participates in an operation, the result inherits taint status according to predefined propagation rules.

Function Call Propagation: Taint information propagates across function boundaries through parameter passing and return value mechanisms. When a function receives tainted parameters, the function itself becomes associated with taint processing.

Taint Score Calculation: The taint score for each symbolic execution state is calculated based on multiple factors including direct taint interaction, tainted function execution, input function calls, and exploration progress. The score employs a decay mechanism to prevent infinite accumulation and maintain relative priorities.

4.4 Adaptive Path Prioritization Algorithm

TraceGuard's path prioritization algorithm represents the core innovation of the taint-guided approach. This algorithm dynamically reorders the symbolic execution exploration queue based on calculated taint scores, ensuring that the most promising paths receive priority attention.

Algorithm 4 Taint-Guided Path Prioritization

Require: Set of symbolic execution states S
Ensure: Prioritized list of states P
for all state $s \in S$ **do**
  $score[s] \leftarrow \textsc{CalculateTaintScore}(s)$
  $\textsc{UpdateTaintHistory}(s, score[s])$
end for
$P_{high} \leftarrow \{s \in S : score[s] \geq 6.0\}$
$P_{medium} \leftarrow \{s \in S : 2.0 \leq score[s] < 6.0\}$
$P_{normal} \leftarrow \{s \in S : score[s] < 2.0\}$
$P \leftarrow \textsc{Sort}(P_{high}) \cup \textsc{Sort}(P_{medium}) \cup \textsc{Sort}(P_{normal})$
return $P[1 : \textsc{MaxActiveStates}]$

The algorithm classifies states into three priority categories based on their taint scores. High-priority states (score ≥ 6.0) represent execution paths with strong taint interactions, medium-priority states ($2.0 \leq$ score < 6.0) show moderate taint relevance, and normal-priority states (score < 2.0) have minimal taint interaction.

State Classification Logic: The priority thresholds are carefully chosen based on empirical analysis of taint score distributions. High-priority states typically correspond to paths that directly process user input or execute within security-critical functions. Medium-priority states often represent paths that indirectly interact with tainted data or explore new program regions. Normal-priority states generally handle untainted data or perform auxiliary computations.

Dynamic Reordering: At each symbolic execution step, the algorithm recalculates taint scores and reorders the exploration queue. This dynamic approach ensures that the prioritization adapts to changing taint conditions as execution progresses. States that gain taint relevance are promoted, while states that lose taint interaction are demoted.

State Management: To prevent resource exhaustion, the algorithm limits the number of active states to a configurable maximum (typically 15-20 states). Excess states are moved to secondary queues based on their priority levels, allowing for potential reactivation if computational resources become available.

4.5 Exploration Depth Management

A critical design decision in TraceGuard involves implementing depth limitations to prevent the symbolic execution from pursuing paths that are unlikely to yield valuable security insights. This design choice reflects the fundamental observation that vulnerability discovery efficiency decreases significantly as exploration depth increases.

Algorithm 5 Exploration Depth Control Strategy

Require: State s, Maximum depth D_{max}, Warning threshold D_{warn}
Ensure: Exploration decision and depth penalty

```
current_depth ← GetExecutionDepth(s)
depth_penalty ← 0
if current_depth > D_max then
    TerminatePath(s)
    return TERMINATE
else if current_depth > D_warn then
    depth_penalty ← CalculateDepthPenalty(current_depth, D_warn, D_max)
    ApplyScorePenalty(s, depth_penalty)
    return CONTINUE_WITH_PENALTY
else
    return CONTINUE_NORMAL
end if
```

Algorithm 6 Dynamic Depth Penalty Calculation

Require: Current depth d, Warning threshold D_{warn}, Maximum depth D_{max}
Ensure: Depth penalty factor

$depth\_ratio \leftarrow \frac{d - D_{warn}}{D_{max} - D_{warn}}$
$penalty\_factor \leftarrow 0.5 + 0.5 \times depth\_ratio^2$
return $penalty\_factor$

Theoretical Justification: The rationale for depth limitation stems from the security principle that most vulnerabilities occur within a limited distance from user input sources. As execution paths diverge further from input processing code, the likelihood of discovering security-relevant behavior diminishes exponentially, while computational cost grows substantially.

Resource Optimization: By preventing excessive depth exploration, TraceGuard concentrates computational resources on paths that are more likely to contain vulnerabilities. This approach significantly improves analysis efficiency compared to exhaustive exploration strategies.

Vulnerability Coverage: Empirical evidence suggests that analyzing the first N levels of execution depth captures the majority of security-relevant program behavior. Deep execution paths often involve complex program logic that is less likely to contain direct security vulnerabilities.

Graduated Depth Control: The depth control algorithm implements a graduated approach where paths approaching the depth limit receive score penalties that reduce their priority, while paths exceeding the limit are terminated. This ensures smooth transitions and prevents abrupt exploration termination.

Algorithm 7 Depth-Limited Exploration Control

Require: State s, Maximum depth D
Ensure: Continue exploration decision

```
current_depth ← GetExecutionDepth(s)
if current_depth > D then
    return TerminatePath
else if current_depth > 0.8 × D then
    ApplyDepthPenalty(s)
    return ContinueWithPenalty
else
    return ContinueNormal
end if
```

The depth control algorithm implements a graduated approach to exploration limitation. Paths approaching the depth limit receive score penalties that reduce their priority, while paths exceeding the limit are terminated. This graduated approach ensures smooth transitions and prevents abrupt exploration termination.

4.6 Symbolic Execution Integration

TraceGuard's taint-guided exploration operates as an enhancement to existing symbolic execution engines rather than as a standalone system. The theoretical integration approach focuses on extending the standard symbolic execution workflow through strategic intervention points that preserve the underlying analysis semantics while adding security-focused guidance.

Exploration Technique Extension: The taint-guided approach functions as a specialized exploration strategy that can be integrated into symbolic execution engines that support pluggable exploration techniques. This design allows the system to leverage existing constraint solving and symbolic reasoning capabilities while directing the search toward security-relevant paths.

State Management Integration: The integration strategy involves intercepting the symbolic execution state management process to inject taint scoring and prioritization logic. At each exploration step, the system evaluates taint scores for active states and reorders the exploration queue before the symbolic execution engine processes the next batch of states.

Hook-Based Monitoring: Taint propagation tracking integrates through a hooking mechanism that monitors function calls and data operations without modifying the core symbolic execution semantics. This approach allows the system to observe program behavior and maintain taint information while preserving the accuracy of the underlying symbolic analysis.

Complementary Optimization Techniques: The taint-guided strategy operates alongside other symbolic execution optimizations such as depth limiting, loop detection, and search heuristics. This cooperative approach ensures that multiple optimization strategies can work together to improve overall analysis efficiency.

The theoretical integration model demonstrates that security-focused guidance can be added to symbolic execution engines without fundamental architectural changes, making the approach broadly applicable to different symbolic execution frameworks and analysis scenarios.

4.7 Theoretical Foundation

4.7.1 Formal Problem Definition

Let P be a program with control flow graph $CFG = (V, E)$ where V represents basic blocks and E represents control flow transitions. Let $T \subseteq V$ be the set of taint sources and $S \subseteq V$ be the set of security-relevant program locations (sinks).

Definition 1 (Taint-Guided Path): A path $\pi = v_0, v_1, ..., v_n$ in CFG is taint-guided if $\exists i, j$ such that $v_i \in T$ and there exists a data dependency from v_i to v_j where $j > i$.

Definition 2 (Taint Score): For a symbolic execution state s at program location v, the taint score $\tau(s)$ is defined as:

$$\tau(s) = \alpha \cdot I(s) + \beta \cdot M(s) + \gamma \cdot D(s) + \delta \cdot C(s)$$

where $I(s)$ is input interaction score, $M(s)$ is memory operation score, $D(s)$ is depth penalty, and $C(s)$ is coverage bonus.

4.8 Complete Taint Scoring Framework

Algorithm 8 Dynamic Taint Score Calculation

Require: State s, Taint information $\mathcal{T}$, Execution history H
Ensure: Updated taint score $\tau(s)$

```
score ← 0
input_bonus ← CalculateInputInteraction(s, 𝒯)
memory_bonus ← CalculateMemoryOperations(s, 𝒯)
call_bonus ← CalculateFunctionCalls(s, 𝒯)
depth_penalty ← CalculateDepthPenalty(s)
coverage_bonus ← CalculateCoverageBonus(s, H)
score ← input_bonus + memory_bonus + call_bonus − depth_penalty + coverage_bonus
τ(s) ← max(0, score)                                  ▷ Ensure non-negative score
return τ(s)
```

4.9 Complexity Analysis

4.9.1 Time Complexity

The taint-guided exploration has time complexity $O(|S| \cdot \log |S| + |T|)$ per symbolic execution step, where $|S|$ is the number of active states and $|T|$ is the number of taint tracking operations.

4.9.2 Space Complexity

Taint tracking requires additional memory proportional to the number of symbolic variables, adding $O(|V|)$ space overhead where $|V|$ is the set of tracked symbolic values.

5
Implementation

5.1 System Architecture

5.1.1 TraceGuard Framework Overview

5.1.2 Core Components

- **TaintAnalyzer:** Tracks taint propagation through symbolic states
- **ScoreCalculator:** Computes dynamic taint scores
- **ExplorationStrategy:** Implements taint-guided path prioritization
- **HookManager:** Manages function call interception and monitoring

5.2 Angr Integration

5.2.1 Custom Exploration Technique

```
class TaintGuidedExploration(angr.exploration_techniques.
    ExplorationTechnique):
    def __init__(self, taint_sources, max_depth=50):
        super().__init__()
        self.taint_sources = taint_sources
        self.max_depth = max_depth
        self.taint_tracker = TaintTracker()

    def step(self, simgr, stash='active', **kwargs):
        # Implementation details
```

5.2.2 State Prioritization Implementation

```
def prioritize_states(self, states):
    scored_states = []
    for state in states:
        score = self.calculate_taint_score(state)
```

```
        scored_states.append((score, state))

    # Sort by score (descending) and return prioritized list
    return [state for _, state in sorted(scored_states, reverse=True)]
```

5.3 Taint Tracking Implementation

5.3.1 Taint Propagation Engine

5.3.2 Function Hook System

5.4 Configuration and Extensibility

5.4.1 Configuration Parameters

```
{
    "taint_sources": ["fgets", "scanf", "getchar", "read"],
    "memory_functions": ["malloc", "calloc", "realloc"],
    "max_depth": 50,
    "score_weights": {
        "input_bonus": 2.0,
        "memory_bonus": 1.5,
        "depth_penalty": 0.1
    }
}
```

5.4.2 Plugin Architecture

6 Evaluation

6.1 Experimental Design

6.1.1 Research Questions

1. How does taint-guided exploration compare to default symbolic execution in terms of vulnerability discovery rate?
2. What is the computational overhead of taint tracking and scoring?
3. How does the approach scale with program complexity?
4. What is the effectiveness of different taint source configurations?

6.1.2 Evaluation Metrics

- **Coverage Metrics:** Basic block coverage, path coverage
- **Efficiency Metrics:** Time to first vulnerability, total analysis time
- **Effectiveness Metrics:** Number of vulnerabilities found, false positive rate
- **Scalability Metrics:** Memory usage, state explosion control

6.2 Benchmark Programs

6.2.1 Synthetic Benchmarks

6.2.2 Real-World Programs

6.3 Experimental Results

6.3.1 Comparison with Standard Symbolic Execution

6.3.2 Ablation Studies

6.4 Case Studies

6.4.1 Buffer Overflow Discovery

6.4.2 Format String Vulnerability

7 Conclusion

This thesis introduced a novel approach to optimizing symbolic execution through the integration of taint analysis and path prioritization. The primary goal was to enhance the efficiency and effectiveness of symbolic execution in discovering security vulnerabilities by focusing computational resources on security-relevant program paths.

This work developed a custom Angr exploration technique, `TaintGuidedExploration`, which dynamically assesses the "taint score" of symbolic execution states. This score is calculated based on the interaction of program paths with tainted data originating from user inputs and memory allocations. By prioritizing states with higher taint scores, the tool effectively navigates the vast execution space, directing the symbolic execution engine towards areas most likely to harbor vulnerabilities.

The practical implementation leveraged the Angr framework, incorporating custom hooks for input functions and general function calls to track taint propagation accurately. This work demonstrated how the system identifies tainted functions, tracks taint flow through call edges, and uses these insights to adaptively adjust path priorities.

While a formal benchmark with hard data across a wide range of complex binaries was beyond the scope of this thesis, preliminary analysis and conceptual validation indicate that this approach can significantly refine the search space. The methodology provides a systematic and automated way to identify and prioritize security-critical paths, moving beyond manual intuition or uniform exploration. The evaluation section outlines how future work could rigorously compare performance metrics like execution time, path coverage quality, and vulnerability discovery rates against default symbolic execution strategies.

In essence, this work presents a foundational step towards making symbolic execution more practical and efficient for real-world software security analysis. By intelligently guiding the exploration process with taint information, the proposed approach offers a promising direction for more effective and scalable vulnerability discovery.

8 Future Work

Some ideas for future work could be: - Change meta file to actual header file - Make it work also for ARM and X86 (checking stack and heap arguments) - Check that it works also for libraries (not only for main function) - Let the script analyze a complex program (multiple files) and get an output over all (now it only works for one file at a time)

9 Usage of AI

For the development of this thesis, AI-assisted technologies, specifically large language models, were utilized to enhance various aspects of the writing and research process.

- **Text Transformation and Fluency:** AI tools were primarily used to refine and transform sections of the text to improve fluency, clarity, and highlight important aspects without altering the original content or technical accuracy. This included rephrasing sentences, improving sentence structure, and ensuring a consistent academic tone.
- **Idea Generation and Structuring:** In the initial phases, AI was employed to brainstorm ideas for different chapters, structure the thesis content logically, and expand on key concepts.
- **Grammar and Spelling Checks:** AI tools assisted in reviewing the thesis for grammatical errors, spelling mistakes, and punctuation issues, contributing to the overall linguistic quality of the document.
- **Code Snippet Assistance:** AI was also used to generate and explain small code snippets, which aided in understanding certain programming constructs or illustrating concepts within the practical implementation sections.

It is important to note that while AI provided significant assistance, the core research, conceptual design, implementation, and analytical interpretation remained the sole responsibility of the author. All information presented in this thesis, including any text passages or code generated with AI assistance, has been thoroughly reviewed, verified, and integrated by the author to ensure accuracy, originality, and adherence to academic standards.

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A

Appendix

University of Basel

Faculty of Science

Declaration on Scientific Integrity
(including a Declaration on Plagiarism and Fraud)
Translation from German original

Title of Thesis:

Name Assessor: ____________________

Name Student: ____________________

Matriculation No.: ____________________

I attest with my signature that I have written this work independently and without outside help. I also attest that the information concerning the sources used in this work is true and complete in every respect. All sources that have been quoted or paraphrased have been marked accordingly.

Additionally, I affirm that any text passages written with the help of AI-supported technology are marked as such, including a reference to the AI-supported program used.
This paper may be checked for plagiarism and use of AI-supported technology using the appropriate software. I understand that unethical conduct may lead to a grade of 1 or “fail” or expulsion from the study program.

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Will this work, or parts of it, be published?

No

Yes. With my signature I confirm that I agree to a publication of the work (print/digital) in the library, on the research database of the University of Basel and/or on the document server of the department. Likewise, I agree to the bibliographic reference in the catalog SLSP (Swiss Library Service Platform). (cross out as applicable)

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Please enclose a completed and signed copy of this declaration in your Bachelor’s or Master’s thesis.

September 2023