

YASA: Scalable Multi-Language Taint Analysis on the Unified AST at Ant Group

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Abstract

Modern enterprises increasingly adopt diverse technology stacks with various programming languages, posing significant challenges for static application security testing (SAST). Existing taint analysis tools are predominantly designed for single languages, requiring substantial engineering effort that scales with language diversity. While multi-language tools like CodeQL, Joern, and WALA attempt to address these challenges, they face limitations in intermediate representation design, analysis precision, and extensibility, which make them difficult to scale effectively for large-scale industrial applications at Ant Group. To bridge this gap, we present YASA (Yet Another Static Analyzer), a unified multi-language static taint analysis framework designed for industrial-scale deployment. Specifically, YASA introduces the Unified Abstract Syntax Tree (UAST) that provides a unified abstraction for compatibility across diverse programming languages. Building on the UAST, YASA performs point-to analysis and taint propagation, leveraging a unified semantic model to manage language-agnostic constructs, while incorporating language-specific semantic models to handle other unique language features. When compared to 6 single- and 2 multi-language static analyzers on an industry-standard benchmark, YASA consistently outperformed all baselines across Java, JavaScript, Python, and Go. In real-world deployment within Ant Group, YASA analyzed over 100 million lines of code across 7.3K internal applications. It identified 314 previously unknown taint paths, with 92 of them confirmed as 0-day vulnerabilities. All vulnerabilities were responsibly reported, with 76 already patched by internal development teams, demonstrating YASA’s practical effectiveness for securing large-scale industrial software systems.

1 Introduction

Modern software systems increasingly adopt polyglot programming paradigms [1, 46, 47], leveraging multiple programming languages across various layers and components to address rapidly evolving business and technological requirements [37, 38]. Recent surveys and empirical studies [36, 64, 72] have revealed that over 80% of large-scale applications utilize two or more programming languages in production environments. As one of the world’s leading financial

technology platforms, Ant Group also relies on a diverse technology stack to support its business-critical applications. For example, microservices-based infrastructures often implement backend services in Java or Go due to their scalability and performance, while employing JavaScript, TypeScript, or popular frontend frameworks like React and Vue for user interface development [56]. This diversity in programming languages and frameworks enables organizations like Ant Group to harness the strengths of each technology for specific tasks, but it also introduces significant challenges in software development and maintenance [11, 35, 59].

Static Application Security Testing (SAST) has emerged as a fundamental approach for identifying vulnerabilities in software systems, with static taint analysis representing one of the most effective and widely adopted technique [4, 27, 43, 58]. Extensive research from both academia [33, 34, 58, 63] and industry [68, 70, 71] has demonstrated the efficacy of static analysis in detecting various taint-style vulnerabilities, including code/command injection [15, 48, 52], SQL injection [30], deserialization [13, 51], server-side request forgery (SSRF) [28, 39], and prototype pollution [31, 33, 34]. Despite these achievements, a critical challenge remains: are these static taint analysis tools truly engineered for industrial-scale, multi-language development practices?

Research Gaps. One of the most critical limitations is that most academic taint analysis tools are designed as language-specific prototypes, lacking extensibility and portability. Representative tools such as FlowDroid [4] and Tai-e [63] for Java, SVF [14, 62] and Infer [18] for C/C++, TAJS [27, 32], DoubleX [20], ODGen [31, 33, 34], and GraphJS [21] for JavaScript, PyT [53] and Pysa [19] for Python, Tchecker for PHP [8, 43], and ARGOT [7] for Go require dedicated engineering effort for each target language. This approach of using language-specific analysis tools introduces several critical challenges that severely limit their applicability in industrial settings [3, 12]. First, development and maintenance costs are substantially increased because each language requires independent analysis frontends, dedicated dataflow engines, separate rule sets, and specialized expertise [16, 29]. As the number of supported languages grows, engineering efforts scale linearly, resulting in duplicative and inefficient workflows across teams [54]. Secondly, the management and aggregation of analysis results become complicated. Outputs from different tools are often stored in incompatible formats [29, 44, 49], which prevents consolidation into a unified security knowledge base. Finally, as new programming languages

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and frameworks are continuously adopted in production, building and maintaining separate analysis capabilities for each new stack is unsustainable [54], resulting in coverage gaps and missed opportunities to secure the latest workflows.

In response, state-of-the-art industrial solutions have emerged to support multi-language taint analysis, most notably CodeQL [17, 22], Joern [8, 71], WALA [55, 66], Infer [18], and Semgrep [57]. However, despite their popularity and wide adoption, these frameworks face inherent limitations. First, from the architectural perspective, designing a unified intermediate representation (IR) that is both sufficiently expressive and extensible across multiple programming languages is intrinsically challenging [60, 61]. This inherent difficulty in IR unification will be discussed further in § 2.2. Second, these tools struggle to maintain high precision across languages, such as context-, path-, field-, and flow-sensitivity. Third, extensibility remains a challenge, as integrating new frameworks or language features into these multi-language platforms often demands substantial re-engineering effort [26], limiting their adaptability in rapidly evolving software environments. As such, there remains an urgent research and engineering gap in designing scalable and precise taint analysis frameworks truly suited for the multi-language realities of modern enterprise software.

Our Work. To address these challenges, we present YASA (Yet Another Static Analyzer), a unified multi-language static taint analysis framework. Specifically, YASA introduces the Unified Abstract Syntax Tree (UAST) as a unified IR that abstracts and normalizes core language constructs across different programming languages. Our key insight is that while programming languages exhibit significant syntactic and semantic differences, the fundamental concepts underlying taint propagation, such as variable assignments, function calls, control flow, and data dependencies, can be abstracted into a unified computational model that preserves language-specific semantics while enabling cross-language reuse. Therefore, building on the UAST, YASA performs point-to analysis and taint propagation, which combines language-agnostic common semantic models with language-specific semantic handlers to address unique features, such as Python’s duck typing or JavaScript’s prototype chains. In summary, YASA’s architecture consists of three core components: (1) *Language Frontend Processors* that transform language-specific ASTs into UAST, (2) a *Unified Semantic Analyzer* that implements context-, path-, and field-sensitive point-to analysis on the UAST, and (3) *Language-Specific Semantic Handlers* that address unique language characteristics.

Evaluation. We conducted a comprehensive evaluation to demonstrate YASA’s effectiveness, extensibility, and practicality. To evaluate the effectiveness, we compared YASA against 6 state-of-the-art (SOTA) single-language analyzers (e.g., Tai-e [63], PySA [19], ODGen [34]) and 2 popular multi-language frameworks (CodeQL [22], Joern [71]) on an industry-standard xAST benchmark to evaluate the soundness and completeness (RQ1). Based on our evaluation, YASA consistently outperformed all baselines across Java, JavaScript, Python, and Go. For instance, it surpassed the best-performing single-language tools by up to 27% in soundness evaluation (for Go) and 32% in completeness evaluation (for JavaScript). Against multi-language frameworks like CodeQL and Joern, YASA improves the soundness by an average of 24.4% and completeness

by 24.9% across all tested languages. To quantify language extensibility, we show that YASA’s language-agnostic semantic analyzer achieves 77.3% average code reuse across four languages, requiring only 16.1% to 26.8% additional effort for language-specific handlers, while maintaining strong standalone performance with up to 77% passes in benchmark cases without language-specific enhancements. To prove real-world practicality, we deployed YASA at Ant Group, analyzing over 100 million lines of code across 7,300 multi-language applications (RQ3). YASA identified 314 previously unknown vulnerability paths, from which security experts confirmed 92 as 0-day vulnerabilities, including code/command injection, SQL injection, SSRF, and insecure serialization. We have responsibly reported these vulnerabilities, and 76 of them have been fixed by developers.

Contributions. To summarize, we make the following contributions in this paper:

- **Unified Multi-Language IR Design.** We propose UAST, a novel representation to address the challenge of multi-language semantic unification. We have implemented frontend parsers for 4 programming languages, and both the specifications and these parsers have been fully open-sourced at <https://github.com/antgroup/YASA-UAST>.
- **Scalable Taint Prototypes.** Building on UAST, we design and implement YASA, a multi-language taint analysis framework that achieves context-, path-, and field-sensitive taint propagation. This analyzer has been fully open-sourced at <https://github.com/antgroup/YASA-Engine>.
- **Real-World Impact.** We analyze over 100 million lines of code across 7.3K applications at Ant Group. YASA has reported 314 previously unknown taint paths, with 92 of them confirmed as 0-day vulnerabilities. We have responsibly disclosed them, with 76 already patched by developers.

2 Background and Motivation

2.1 Multi-language Taint Analysis

Modern multi-language taint analysis frameworks such as CodeQL [22], Joern [71], and WALA [66] adopt distinct approaches to support diverse programming languages. As illustrated in Figure 1, CodeQL employs a database-centric method, transforming source code into language-specific databases for analysis using declarative SQL queries [6]. These databases capture annotated ASTs and semantic details, but require language-specific extractors and SQL libraries (.ql1). Joern, in contrast, uses a graph-based Code Property Graph (CPG) [71], a unified intermediate representation combining AST, CFG, and PDG. Language-specific frontends generate CPGs, which are enriched with semantic passes for taint propagation. WALA relies on existing parsers and runtime environments (e.g., Rhino, Jython) to convert source code into a Common Abstract Syntax Tree (CAST), further processed into control flow graphs and SSA form for interprocedural analysis [55].

Limitations in Practice. Despite their strengths, these frameworks face notable limitations. CodeQL’s reliance on language-specific extractors and database schemas results in significant fragmentation: as shown in Table 1, only 4.5% of its codebase is language-agnostic,

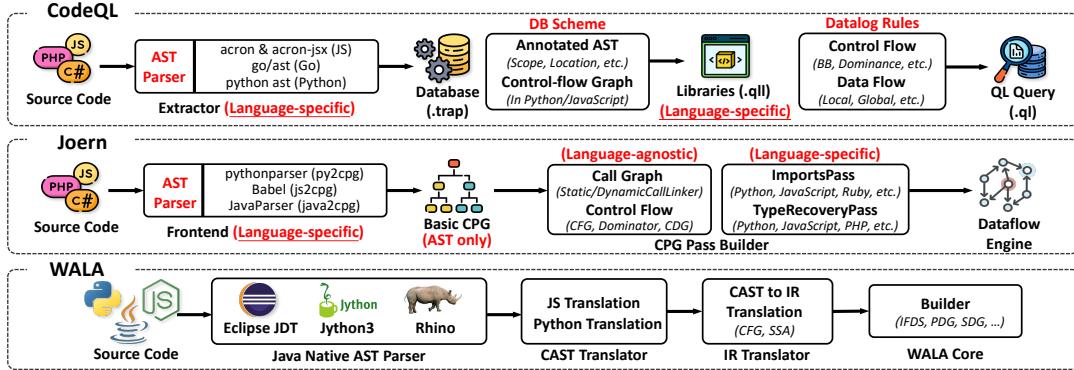


Figure 1: Architectural Comparison of CodeQL, Joern, and WALA for Multi-language Taint Analysis.

Table 1: #LoC Distribution in CodeQL Between Language-Specific and Language-Agnostic Components

Category	Language	Extractor	Library
Language-Specific	JavaScript	40,467	106,371
	Java/Kotlin	10,966 [†]	69,118
	C/C++	N/A [†]	134,628
	C#	31,590	54,301
	Python	26,995	67,003
	Go	8,604	31,157
Total		118,622	462,578
Language-Agnostic	/	27,492 (4.5%)	

[†] The extractors for Java and C/C++ are not open source; only the Kotlin extractor is publicly available.

making it costly to extend support for new languages. Joern's over-abstraction in CPG inflates representation size and reduces precision for dynamic language features like JavaScript's prototype chains and Python's runtime modifications [34]. WALA, originally designed for Java bytecode, struggles with modern dynamic languages due to its dependence on interpreters (e.g., Rhino, Jython) and SSA-based representations, which fail to capture advanced semantics. These limitations will be discussed in § 2.2.

2.2 Intermediate Representation

The choice of IR determines the effectiveness, precision, and extensibility of multi-language static analysis frameworks. Typical forms include AST, CFG, SSA, PDG, and their various cross-combinations. Each form provides a different abstraction level and caters to specific analysis requirements.

Single-Language IR Characteristics. Single-language static analysis tools often employ IRs tailored to the semantic properties of their target languages, enabling high-precision analysis but sacrificing cross-language compatibility. As illustrated in Table 2, compiled languages like C/C++ and Java predominantly favor register-based SSA forms that naturally align with their static compilation models. SVF leverages LLVM IR with specialized Pointer Assignment Graph (PAG) and Sparse Value-Flow Graph (SVFG) extensions to handle

Table 2: IRs Used in Single- and Multi-language SASTs.

Type	Tool: IR	Vocabulary	Syntax
Single	SVF [62]: SVF IR (LLVM IR)	Register	PAG, SSA, SVFG
	Tai-e [63]: Tai-e IR (Jimple)	Register	SSA
	Doop [24]: WALA/Soot IR	Register	SSA
	TAJS [27]: AST (jscmp, Babel)	AST Node	AST
	ODGen [34]: AST (esprima)	AST Node	AST
	DoubleX [20]: AST (esprima)	AST Node	AST, CFG, PDG
	GraphJS [21]: AST (estree)	AST Node	AST, CFG, MDG
	PyT [53]: AST (python ast)	AST Node	AST, CFG
Multi	Pysa [19]: AST (python ast)	AST Node	AST, CFG
	ar-go-tools [7]: Go SSA	Register	SSA
	CodeQL [22]: Database (.trap)	DB Scheme	AST, CFG
	CodeFuse-Query [70]: Database	DB Scheme	AST, CFG
	Joern [71]: CPG	AST Node	AST, CFG, PDG
	WALA [66]: WALA IR	CAST & Register	AST, CFG, SSA
	LLVM [42]: LLVM IR	Register	SSA
	Infer [18]: SIL	AST Node	AST, CFG

complex pointer relationships and memory operations characteristic of C/C++ programs [62]. Similarly, Java-focused tools like Tai-e and Doop utilize register-based SSA representations (Tai-e IR and Jimple respectively) [24, 63]. In contrast, dynamic languages such as JavaScript and Python favor AST-based representations that preserve high-level semantics critical for handling dynamic features like prototype chains, runtime attribute modification, and complex scoping rules. Tools like ODGen [34], DoubleX [20], PyT [53], and Pysa [19] rely on ASTs augmented with control flow information for effective analysis.

Multi-Language IRs and Trade-offs. Multi-language analysis frameworks face the challenge of balancing expressiveness, precision, and cross-language compatibility. As shown in Table 2, existing approaches can be categorized into three primary strategies.

Database-relational unification, such as CodeQL [22] and CodeFuse-Query [70], transforms source code into queryable database schemas, which enables powerful declarative queries through relational database operations. However, in § 2.1, we demonstrate that each language requires independent schema design and analysis logic, leading to substantial engineering overhead that scales linearly with the number of supported languages.

Graph-based unification, represented by Joern's CPG, attempts to create a unified graph structure combining AST, CFG, and PDG

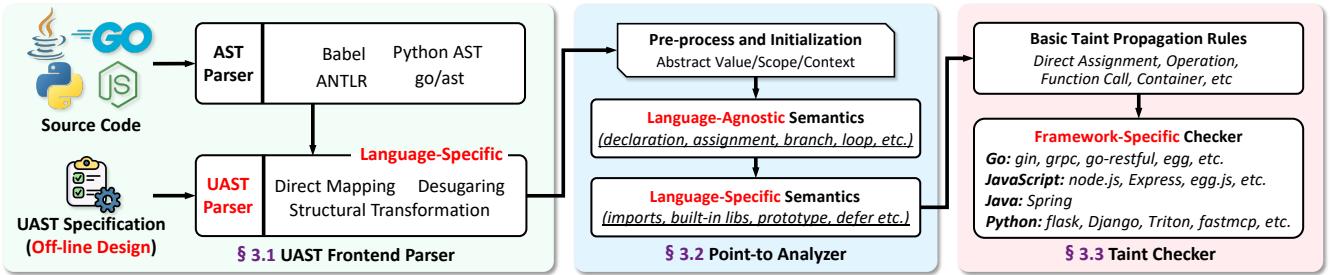


Figure 2: Architecture Overview of YASA.

information across languages [71]. While this approach provides intuitive graph traversal capabilities for analysis queries and enables some degree of cross-language analysis reuse, the CPG specification suffers from limitations due to its over-abstraction of high-level language features. The core issue lies in CPG’s “lowering” strategy, where complex language constructs are decomposed into simpler, more primitive node combinations to fit the limited CPG vocabulary, leading to significant semantic information loss and representation bloat. For example, a simple Python class definition node is decomposed in CPG into tens of nodes involving TYPE_DECL nodes, synthetic METHOD nodes, and <metaClassCallHandler> for handling class semantics, and so on. Moreover, due to the limited vocabulary, the CPG specification fails to express some specific structures, such as `yield` expression in Python.

Low-level register-based unification, including WALA and LLVM, achieves cross-language compatibility by operating at reduced abstraction levels using register-based SSA representations [42, 66]. WALA transforms source code through language-specific interpreters into a common SSA form, enabling shared analysis algorithms across Java, JavaScript, and Python. LLVM IR operates at an even lower level, providing a register-based SSA representation that supports C/C++ and Go through their respective compiler frontends. While these approaches enable significant code reuse in analysis algorithms, they struggle with dynamic language features, where JavaScript’s prototype, Python’s runtime attribute modification, and dynamic method dispatch cannot be accurately captured in static SSA designed for traditional compiled languages.

Insights & Challenges. Despite these limitations, existing multi-language approaches offer valuable insights into effective IR design. Notably, almost all successful multi-language frameworks incorporate AST as the foundational component: CodeQL extracts AST information into database schemas, Joern’s CPG builds upon AST structures, and WALA begins with CAST before lowering to SSA. These practices suggest that AST-based representations offer advantages for multi-language unification by naturally preserving high-level semantic information. However, the critical challenge lies in determining the appropriate level of abstraction for cross-language compatibility. A key lesson learned from CPG is that over-abstraction with a limited vocabulary can unnecessarily complicate simple language constructs while failing to express certain language-specific features. Therefore, successful AST-based multi-language IR requires achieving the balance between cross-language compatibility and language-specific semantic preservation.

3 Methodology

We present YASA (Yet Another Static Analyzer), a scalable and extensible multi-language static taint analysis framework designed to address cross-language compatibility challenges and large-scale codebase analysis. Specifically, YASA utilizes the UAST, an offline-designed specification that unifies diverse language constructs into a common representation while preserving semantic fidelity. As shown in Figure 2, YASA consists of three key components. The *UAST Frontend Parser* transforms language-specific ASTs into the UAST format through direct mapping, structural transformations, and desugaring, enabling consistent cross-language analysis. The *Point-to Analyzer* performs pointer analysis by integrating language-agnostic semantics for common constructs such as assignments, branches, and loops, with language-specific extensions for unique features like Python decorators, Go’s ‘`defer`’, and JavaScript’s prototype chain. Finally, the *Taint Checker* tracks taint flows using basic propagation rules (e.g., assignments, operations, function calls) and adapts to real-world frameworks such as Flask, Spring, and Express through the customized *Framework-Specific Checker*. This modular architecture ensures semantic fidelity, maximizes algorithm reuse, and supports precise and scalable taint analysis across multi-language environments.

3.1 UAST Frontend Parser

3.1.1 Design of UAST Specification. The core of YASA’s multi-language unification lies in its UAST, which is designed to achieve both broad compatibility and precise semantic representation across diverse programming languages. To accomplish this, we conducted an in-depth analysis of the syntax and semantic constructs in multiple languages, identifying common patterns as well as language-specific peculiarities, which provided the foundation for constructing a unified node taxonomy. As shown in Table 3, we classified AST nodes from different programming languages into three categories to heuristically design this specification: *Universal Semantic Nodes*, *Language-Specific Nodes*, and *Reducible Nodes*.

Type#1: Universal Semantic Nodes. Universal semantic nodes represent constructs that share equivalent semantics across at least two supported languages, even if their syntax differs. These nodes enable consistent representation across languages and facilitate the reuse of analysis logic built on top of this unified structure. Examples include core programming constructs such as basic operations (Literal, Identifier, BinaryExpression), control flow

Table 3: Classification of AST Nodes and Language Constructs Across Different Programming Languages.

Category	AST Node	Description
Universal	Literal	Constant values (e.g., numbers, strings)
	BinaryExpression	Binary operations (e.g., +, -, ==)
	IfStatement	Conditional branching
	CallExpression	Function or method invocation
Specific	RangeStatement	Unified iteration construct
	YieldExpression	Generator functions in Python
	ChanType	Channel constructs in Go
	TupleExpression	Tuple constructs in Python
Reducible	[x for x in list]	→ VariableDeclaration + RangeStmt
	() => expr	→ FunctionDefinition
	Expression	Root node for expressions in Python
	Comment	Comment nodes in Go

statements (IfStatement, WhileStatement), and universal declarations (FunctionDefinition, VariableDeclaration). By focusing on semantic equivalence rather than syntactic representation, these nodes normalize language variations while preserving their computational meaning. For instance, the RangeStatement unifies iteration constructs like JavaScript's for-of loops, Python's for-in syntax, and Go's range keyword into a single node type with shared semantics.

Type#2: Language-Specific Nodes. Language-specific nodes represent constructs that are unique to a particular language and cannot be easily expressed using universal semantic nodes without significant semantic loss. These nodes are explicitly retained in the UAST Specification to ensure accurate representation of language features that are critical for program analysis. Examples include Python's YieldExpression for generator functions, Go's ChanType for channel constructs, and Python's TupleExpression for tuple representations. These constructs encapsulate essential program semantics that would otherwise be lost if transformed into combinations of other nodes. By preserving these nodes, the UAST balances language-specific precision with a standardized representation across languages.

Type#3: Reducible Nodes. Reducible nodes represent constructs that are either irrelevant to program analysis semantics or can be systematically reduced to equivalent combinations of other nodes without loss of meaning. These nodes are not retained in the UAST specification. For example, Python's list comprehensions ([x for x in list]) can be reduced to a sequence of VariableDeclaration and RangeStatement nodes, while JavaScript's arrow function expression (() => expr) can be transformed into FunctionDefinition nodes. Additionally, redundant nodes such as Python's Expression root node, which serves only as a wrapper for expressions, and Go's Comment node, which represents comments irrelevant to program analysis, are completely discarded during the transformation process. This reduction ensures that the UAST remains compact and analyzable while preserving the expressiveness of high-level language constructs.

Overview of the UAST Specification. The UAST specification encompasses 54 node types distributed across five primary syntactic categories: 4 basic nodes (e.g., literals, identifiers), 16 statement nodes (e.g., control flow, exception handling), 20 expression nodes (e.g., arithmetic operations, function calls), 4 declaration nodes (e.g.,

Table 4: UAST Node Specification by Syntactic Category.

Category	Node Examples	#UNI	#SPEC
Basic Nodes (4)	Noop		
	Literal	4	0
	Identifier		
Statement Nodes (16)	IfStatement		
	ReturnStatement		
	WhileStatement	15	1
	RangeStatement		
Expression Nodes (20)	TryStatement		
	BinaryExpression		
	CallExpression		
	MemberAccess	11	9
Declaration Nodes (4)	NewExpression		
	YieldExpression		
	FunctionDefinition		
	VariableDeclaration	3	1
Type Nodes (10)	ClassDefinition		
	PackageDeclaration		
	PrimitiveType		
	ArrayType		
	PointerType	2	8
	FuncType		
	ChanType		
Total (54)	/	35	19

functions, classes, variables), and 10 type nodes (e.g., static and dynamic type systems). As shown in Table 4, there are 35 universal nodes (65%) providing a shared computational foundation across all languages, and 19 specific nodes (35%) preserving language-specific constructs that possess critical semantic significance. Notably, the classification of language-specific nodes is not fixed. As more languages are supported, some nodes initially categorized as specific may become universal. For example, the current specification retains the DereferenceExpression as a language-specific node for Go. However, if support for C/C++ is added, this node would then serve as a shared construct between Go and C/C++, transitioning to a universal node. This flexibility ensures that the UAST specification continues to evolve as it adapts to the diversity and needs of programming languages.

3.1.2 AST to UAST Transformation. To transform language-specific ASTs into the UAST representation, we developed three distinct transformation rules.

Rule#1: Direct Mapping Rules. Direct mapping rules handle AST nodes that correspond directly to preserved language-specific nodes or universal nodes in the UAST. For language-specific nodes, these rules retain constructs with critical semantics, ensuring their syntax and semantics are preserved. Examples include Python's ast.Yield → YieldExpression and Go's DereferenceExpression, both of which are retained as they represent unique constructs in their respective languages. For universal nodes, direct mapping allows for straightforward conversions without structural modifications, such as Python's ast.If → IfStatement.

Rule#2: Structural Transformation Rules. Structural transformation rules address AST nodes that map to universal nodes in the

UAST but require aggregation or restructuring to unify cross-language variations. These rules transform language-specific structural patterns into semantically equivalent and shared UAST representations, ensuring universal nodes provide a common foundation across languages. Examples include RangeStatement, which serves as a universal representation for loop constructs across languages, such as Python's `ast.For`, JavaScript's `for-of`, Java's enhanced for, and Go's range constructs.

Rule#3: Desugaring Rules. Desugaring rules systematically decompose language-specific syntactic sugar that corresponds to reducible nodes, transforming high-level constructs into equivalent combinations of invariant, aggregated, or preserved UAST nodes. These rules normalize syntactic convenience features into their underlying computational semantics, simplifying representation while preserving semantics. Examples include Python's list comprehensions (`ast.ListComp`) desugared into Sequence nodes, represented as a combination of VariableDeclaration for temporary variables, RangeStatement for iteration, and a final reference to the temporary variable. Similarly, `ast.Lambda` expressions are converted to standard FunctionDefinition nodes, and f-strings (`ast.JoinedStr`) are desugared into BinaryExpression chains.

3.2 Point-to Analyzer

The *Point-to Analyzer* is the core computational engine of YASA, implementing context-sensitive, path-sensitive, and field-sensitive point-to analysis over the unified UAST. The analyzer is designed to handle both language-agnostic semantics and language-specific features through a unified abstraction framework.

3.2.1 Problem Formulation. To enable precise interprocedural point-to analysis across multiple languages, YASA defines three key abstractions: abstract value domain, variable scope, and context state.

Abstract Value Domain. The core of YASA's abstraction is the value domain \mathcal{V} , which represents the abstract values that the variables may point to across different programming languages:

$$\mathcal{V} ::= \text{Prim}(\tau, v) \mid \text{Obj}(\mathcal{H}) \mid \text{Sym}(\tau, n) \mid \text{Phi}(\mathcal{T})$$

where $\text{Prim}(\tau, v)$ represents concrete primitive values with type information τ and concrete value v , such as numbers, strings, and booleans. $\text{Obj}(\mathcal{H})$ abstracts objects and data structures, where the field mapping $\mathcal{H} : \text{Field} \rightarrow \mathcal{V}$ enables field-sensitive analysis by maintaining precise property-to-value relationships. $\text{Sym}(\tau, n)$ represents symbolic values for variables whose concrete references cannot be statically determined, where τ denotes type information and n is the symbolic name identifier. $\text{Phi}(\mathcal{T})$ captures path-sensitive values through a tree structure $\mathcal{T} = (N, E, \lambda)$ where tree nodes N contain values, tree edges E represent control flow transitions, and edge labeling function $\lambda : E \rightarrow \mathcal{P}ath$ annotates each edge with branch conditions, enabling precise tracking of values across different execution branches while preserving path constraints.

Variable Scope Abstraction. Program scopes in YASA function as variable tables that manage the scope state of programs, maintaining variable information contained within all scopes in the current program state. Scopes are organized hierarchically to model lexical scoping relationships and maintain the following abstract structure: $\text{Scope} = \langle \rho, \delta, \sigma_p, \tau_s \rangle$ where $\rho : \text{Var} \rightarrow \mathcal{V}$ maintains variable-to-value mappings for variable lookup and assignment

operations, $\delta : \text{Var} \rightarrow \text{DeclInfo}$ stores variable declaration metadata including type and location information, $\sigma_p \in \text{Scope} \cup \{\perp\}$ points to the parent scope forming hierarchical scope chains, and $\tau_s \in \{\text{Scope}, \mathcal{F}clos, \text{Global}, \text{Uninit}, \text{Sym}\}$ identifies the scope type. YASA defines several specialized scope types to handle different semantic contexts: *General scopes* ($\tau_s = \text{Scope}$) represent standard code blocks and modules with lexical scoping; *Function closures* ($\tau_s = \mathcal{F}clos$) capture function definitions along with their lexical environments, enabling context-sensitive analysis by preserving the binding context at function creation time; *Global scopes* ($\tau_s = \text{Global}$) serve as root scopes in the scope hierarchy, providing the foundation for module-level variable resolution; *Uninitialized variable scopes* ($\tau_s = \text{Uninit}$) represent declared but uninitialized variables, enabling precise tracking of variable lifecycle and detection of use-before-definition errors; and *Symbolic scopes* ($\tau_s = \text{Sym}$) represent unknown or symbolized values that arise when concrete references cannot be statically determined.

Context State Abstraction. The context state in YASA captures execution context information necessary for precise interprocedural analysis, maintaining the complete execution environment required for context-sensitive, path-sensitive analysis across function boundaries. The context state maintains the following abstract structure: $\text{Ctx} = \langle \sigma, \kappa, \pi \rangle$ where $\sigma \in \text{Scope}$ represents the current variable scope containing all variable bindings and scope relationships at the current program point, $\kappa \in \text{Scope}^*$ maintains the function call chain state as a sequence of function closures representing the current call stack for context-sensitive interprocedural analysis, and $\pi \in \mathcal{P}ath^*$ tracks the branch conditions that characterize the current program execution path for path-sensitive reasoning.

3.2.2 Language-Agnostic Operational Semantics. YASA implements context-sensitive, field-sensitive, and path-sensitive point-to analysis over the unified domain. We define the operational semantics using Structural Operational Semantics (SOS) rules that maintain precision across different sensitivity dimensions while enabling cross-language analysis reuse.

$$\frac{\langle f(e_1, \dots, e_n), \text{Ctx} \rangle \Downarrow \langle \mathcal{F}clos, [v_1, \dots, v_n] \rangle \quad \kappa' = \kappa \cdot [\mathcal{F}clos] \wedge |\kappa'| \leq k}{\langle x :^i f(e_1, \dots, e_n), \text{Ctx} \rangle \Downarrow \langle \rho[x \mapsto v_{\text{ret}}], \text{Ctx}' \rangle} \quad (\text{Context Sensitivity})$$

$$\frac{\langle e, \text{Ctx} \rangle \Downarrow \langle v_{\text{test}}, \text{Ctx}' \rangle \quad \text{evaluate}(v_{\text{test}}, \pi) = \text{Unknown}}{\langle \text{if}(e) \{ s_1 \} \text{else} \{ s_2 \}, \text{Ctx} \rangle \Downarrow \langle \text{mergeContexts}(\text{Ctx}_1, \text{Ctx}_2), \text{Ctx}' \rangle} \quad (\text{Path Sensitivity})$$

$$\frac{\langle e, \text{Ctx} \rangle \Downarrow \langle \text{Obj}(\mathcal{H}), \text{Ctx}' \rangle \quad v = \mathcal{H}(f)}{\langle x :^i e.f, \text{Ctx} \rangle \Downarrow \langle \rho[x \mapsto v], \text{Ctx}' \rangle} \quad (\text{Field Sensitivity})$$

Context Sensitivity. YASA maintains calling context through state cloning and call stack extension, enabling precise distinction of function behavior under different calling contexts. The rule maintains calling context through call stack extension $\kappa' = \kappa \cdot [\mathcal{F}clos]$ where each function call creates a new execution state with extended context. Bounded call stack depth prevents infinite recursion while preserving analysis precision.

Path Sensitivity. YASA tracks execution paths by extending path conditions and merging results from different branches, enabling precise reasoning about program behavior under different execution scenarios. The rule implements path-sensitive analysis by forking execution states when branch conditions cannot

be statically determined. Each branch extends path conditions $\pi_T = \pi :: v_{\text{test}}$ and $\pi_F = \pi :: \neg v_{\text{test}}$ to maintain constraints along different execution paths. The `mergeContexts` operation combines results using $\mathcal{P}hi(\mathcal{T})$ values that preserve path-specific information through tree structures.

Field Sensitivity. YASA maintains field-level precision by tracking individual object properties separately, avoiding the imprecision that results from field-insensitive approaches where all fields are merged. The rule maintains field-level precision through the field mapping $\mathcal{H} : \mathcal{F}ield \rightarrow \mathcal{V}$ within object values $Obj(\mathcal{H})$. Field access operations retrieve values through precise field lookups $\mathcal{H}(f)$, while field assignments create updated object values with modified mappings $\mathcal{H}[f \mapsto v]$.

3.2.3 Language-Specific Operational Semantics. While the *Universal Semantic* handles the majority of program constructs through universal UAST nodes, certain language-specific features require specialized semantic handling to maintain analysis precision. YASA addresses this challenge through *Language-Specific Semantic Handlers* that extend the unified analysis framework with targeted support for unique language characteristics.

$$\begin{array}{c} \langle \text{class } C(\text{Base}), Ctx \rangle \Downarrow \langle \text{scope}(C), Ctx' \rangle \quad \text{Base.field}[f] = v \\ \hline \langle C.\text{inherit}(\text{Base}), Ctx \rangle \Downarrow \langle C.\text{field}[f \mapsto v'], Ctx' \rangle \\ \text{(Python)} \end{array}$$

$$\begin{array}{c} \langle \text{obj.method}(), Ctx \rangle \quad \text{obj._proto_.method} \neq \emptyset \\ \hline \langle \text{resolve(method)}, Ctx' \rangle \Downarrow \langle \text{method.call(obj)}, Ctx' \rangle \\ \text{(JavaScript)} \end{array}$$

$$\begin{array}{c} \langle @Data \text{ class } C, Ctx \rangle \Downarrow \langle \text{scope}(C), Ctx' \rangle \quad C.\text{field}[f] \neq \emptyset \\ \hline \langle @Data, Ctx' \rangle \Downarrow \langle C[\text{getF}(), \text{setF}()], Ctx'' \rangle \\ \text{(Java)} \end{array}$$

$$\begin{array}{c} \langle \text{interface } I\{m()\}, Ctx \rangle \Downarrow \langle \text{interface}(I), Ctx' \rangle \quad T.\text{methods}[m] \neq \emptyset \\ \hline \langle T \text{ implements } I, Ctx' \rangle \Downarrow \langle T \subseteq I, Ctx'' \rangle \\ \text{(Go)} \end{array}$$

Each language handler addresses distinctive challenges through specialized semantic rules. Due to space limitations and the diversity of language features, we introduce one representative characteristic for each language. The *Python handler* implements class inheritance resolution by systematically processing base class hierarchies and copying field definitions with proper `_this` binding, enabling accurate analysis of Python's multiple inheritance and method resolution order. The *JavaScript handler* employs prototype injection to transform dynamic prototype relationships into analyzable scope hierarchies, pre-populating prototype chains with built-in methods to enable static analysis of prototype-based method resolution. The *Java handler* processes annotation-driven code generation through metadata-driven semantic injection, automatically transforming annotations like `@lombok.Data` into corresponding getter/setter method implementations within class scopes. The *Go handler* implements structural interface resolution by analyzing method signatures and receiver types to determine implicit interface satisfaction relationships without requiring explicit declarations, maintaining separate method sets for pointer and value receivers to ensure proper interface compatibility semantics.

Notations:

- $v, o \in \mathcal{V}$: Abstract values or objects.
- $f \in \mathcal{F}$: Field names in objects.
- $o_2 \prec o_1$: Object o_2 inherits from object o_1 .
- $\tau_t(v) \in \{\top, \perp\}$: Taint state of v , \top means tainted, and \perp means not.
- s : A program statement (e.g., assignments, function calls, etc.).
- \rightarrow : Denotes taint propagation.

Rules:

1. Assignment Propagation:

$$s : x = y, \tau_t(y) = \top \rightarrow \tau_t(x) = \top$$

2. Container Field Propagation:

$$\begin{aligned} s : o.f = v, \tau_t(v) = \top &\rightarrow \tau_t(o.f) = \top \\ s : x = o.f, \tau_t(o.f) = \top &\rightarrow \tau_t(x) = \top \end{aligned}$$

3. Function Call Propagation:

$$s : z = f(x), \tau_t(x) = \top, \tau_t(\text{return}(f)) = \top \rightarrow \tau_t(z) = \top$$

4. Prototype Propagation (JavaScript):

$$\begin{aligned} s : o_1.\text{prototype}.f = v, \tau_t(v) = \top &\rightarrow \tau_t(o_2.f) = \top, \forall o_2 (o_2 \prec o_1) \\ s : x = o_1.\text{prototype}.f, \tau_t(o_1.\text{prototype}.f) = \top &\rightarrow \tau_t(x) = \top \end{aligned}$$

5. Promise Propagation (JavaScript):

$$\begin{aligned} s : p = \text{Promise.resolve}(v), \tau_t(v) = \top &\rightarrow \tau_t(p) = \top \\ s : q = p.\text{then}(\text{callback}), \tau_t(p) = \top &\rightarrow \tau_t(q) = \top \\ s : v = \text{await } p, \tau_t(p) = \top &\rightarrow \tau_t(v) = \top \end{aligned}$$

6. Channel Propagation (Go):

$$\begin{aligned} s : ch \leftarrow v, \tau_t(v) = \top &\rightarrow \tau_t(ch) = \top \\ s : v = <-ch, \tau_t(ch) = \top &\rightarrow \tau_t(v) = \top \\ s : ch_2 \leftarrow (<-ch_1), \tau_t(ch_1) = \top &\rightarrow \tau_t(ch_2) = \top \end{aligned}$$

Figure 3: Taint Propagation Rules with JavaScript and Go Extensions.

3.3 Taint Checker

The *Taint Checker* in YASA is designed as a highly extensible, plugin-based system for detecting vulnerabilities through taint propagation. Specifically, checkers are implemented as independent, event-driven plugins, allowing users to customize and extend the analysis without modifying core logic. These checkers include *Basic Taint Propagation Rules* and the *Framework-Specific Checker*.

3.3.1 Basic Taint Propagation Rules. The taint analysis in YASA is built upon a modular set of taint propagation rules that define how taint flows between program elements during execution. As summarized in Figure 3, we provide the core propagation rules in YASA. These include basic assignment propagation, container field interactions, function call propagation, and language-specific extensions for JavaScript and Go. For instance, JavaScript-specific rules capture taint propagation through prototypes and promises, while Go-specific rules handle taint flow via channels. The modular design of YASA allows developers to extend or customize these rules to address specific analysis requirements, ensuring flexibility in supporting diverse programming paradigms.

3.3.2 Framework-Specific Checker. Framework-specific checkers in YASA are designed to handle taint propagation patterns unique to specific libraries, frameworks, or APIs. These checkers extend the basic taint propagation rules to account for framework-specific abstractions, such as routing mechanisms, data bindings, and middleware pipelines. For instance, in web frameworks, taint tracking often requires identifying how user inputs flow through routing logic and into application handlers. This includes detecting user-controllable input sources encapsulated by the framework and accurately simulating taint propagation through framework-defined

structures. YASA implements framework-specific checkers that focus on three main tasks: performing taint propagation within framework-specific execution flows, identifying entry points where taint can begin, and defining framework-specific sources to capture user-controlled inputs. For example, in frameworks like Spring-MVC, the checker identifies controller methods as entry points and their parameters as sources. Similarly, in Egg.js, the EggAnalyzer models its unconventional module addressing and routing mechanisms, allowing the checker to track taint from sources such as `this.ctx.request`. By leveraging YASA's modular design, these checkers can be extended or customized to support additional frameworks or APIs, ensuring that YASA remains adaptable to the evolving ecosystem of modern software development.

4 Evaluation

To demonstrate the effectiveness, extensibility, and practicality, we conducted experiments addressing three research questions (RQs):

RQ1: Detection Effectiveness. How does YASA's detection performance compare to existing single-language and multi-language static analysis tools across different programming languages?

RQ2: Language Extensibility. How effectively does YASA's universal design reduce the engineering effort required for integrating each programming language?

RQ3: Real-world Practicality. What is the practical impact of YASA when deployed in production environments for analyzing large-scale multi-language codebases?

4.1 Evaluation Setup

Implementation. We have implemented a prototype of YASA with over 47,000 LoC, excluding any third-party libraries or open-source tools. So far, YASA supports 4 mainstream programming languages used at Ant Group: Python, JavaScript, Java, and Go, covering a total of 16 framework-specific checkers with dedicated taint analysis rules. In Python, YASA supports frameworks such as Flask, Django, and FastAPI. For JavaScript, we provide checkers for frameworks like Express, Egg.js, and Node.js. In Java, YASA includes rules tailored for Spring. For Go, YASA supports popular frameworks like Gin, gRPC, Beego, and Gorilla Mux.

Running Environment All experiments run on an Alibaba Cloud Elastic Compute Service (ECS) instance (`ecs.c6a.16xlarge`). The server operates on Alibaba Cloud Linux 3 and is equipped with 64 vCPUs, 128 GB of RAM, and 4 data disks, each with 8 TB capacity, providing a total storage of 32 TB.

Benchmark. To evaluate the effectiveness, we carefully reviewed several existing benchmarks used for taint analysis. While macro-benchmarks such as OWASP Benchmark [50] and SecBench.js [9] offer real-world scenarios, their heavy reliance on predefined source and sink rules can bias evaluations and obscure tools' core analysis capabilities. These benchmarks also tend to focus on specific vulnerability patterns, making it difficult to isolate a tool's soundness and completeness. On the other hand, micro-benchmarks like Taint-Bench [45] and DroidBench [5] for Android provide fine-grained test cases but are tailored for domains outside YASA's current scope¹. Similarly, micro-benchmarks such as Juliet Test Suite [10] and SecuriBench-Micro [40] are limited to specific languages like

¹YASA does not support Android now

Table 5: Overview of xAST Benchmark Test Cases.

Language	#Soundness [†]	#Completeness [‡]	#Total Cases
JavaScript	134	49	183
Python	252	74	326
Java	111	58	169
Go	105	68	173
Total	602	249	851

[†] #Soundness Case: Test cases evaluating support for language-specific features (e.g., list comprehension in Python, prototype chains or async functions in JavaScript).

[‡] #Completeness Case: Test cases assessing context-, field-, flow-, object-, and path-sensitivity.

C/C++ or Java, making them unsuitable for evaluating YASA's multi-language capabilities. Considering these limitations, we selected xAST² [2], an industrial micro-benchmark designed specifically for evaluating taint analysis tools across multiple programming languages. The benchmark is designed to evaluate both soundness and completeness of taint analysis tools through carefully crafted synthetic test cases. Soundness cases focus on assessing whether the tool comprehensively supports key language-specific features, such as list comprehension in Python or prototypes and asynchronous constructs in JavaScript. These cases ensure the tool can accurately handle complex language constructs without omissions. On the other hand, completeness cases evaluate the tool's sensitivity across various taint analysis dimensions, including context-, field-, flow-, object-, and path-sensitivity. Each test case includes both positive and negative examples: positive examples demonstrate how taint flows from a source to a sink, while negative examples involve non-sensitive inputs that propagate to the sink through secure paths. This distinction prevents tools from achieving artificially high recall rates by simply identifying sink functions through pattern matching, ensuring their true analytical capabilities are rigorously tested. Table 5 provides an overview of xAST's test cases, categorized by programming language. The benchmark covers four widely used languages with a total of 602 soundness cases and 249 completeness cases. This distribution ensures comprehensive coverage of language features and sensitivity dimensions, enabling a robust evaluation of static analysis tools' capabilities.

Baseline. To evaluate RQ1, we select representative single-language and multi-language static taint analysis tools as baselines. For single-language comparisons, we choose SOTA tools for each programming language supported by YASA. For Java, we compare against Tai-e [63] and Doop [24], both of which are widely-recognized academic static analysis frameworks with pointer analysis and taint tracking capabilities. For JavaScript, we evaluate against DoubleX [20] and ODGen [34]. For Python, we compare with Pysa [19], Facebook's production-grade static analyzer that provides comprehensive taint analysis for Python codebases. For Go analysis, we compare against ARGOT [7], a collection of analysis tools for Go developed by AWSLabs. For multi-language baseline comparisons, we select CodeQL [22] and Joern [71], two popular taint analysis frameworks that support multiple programming languages. We

²The "x" in xAST indicates that it can be used for various forms of application security testing, including Static Application Security Testing (SAST), Interactive Application Security Testing (IAST), and Dynamic Application Security Testing (DAST).

Table 6: Detection Performance Comparison on xAST Benchmark

Type	Tool	Java		Go		JavaScript		Python	
		Sound	Complete	Sound	Complete	Sound	Complete	Sound	Complete
	Benchmark	111	58	105	68	134	49	252	74
Single	Doop	59 (53%)	25 (43%)	-	-	-	-	-	-
	Tai-e	75 (68%)	24 (41%)	-	-	-	-	-	-
	ARGOT	-	-	67 (64%)	38 (56%)	-	-	-	-
	DoubleX	-	-	-	-	32 (24%)	15 (31%)	-	-
	ODGen	-	-	-	-	60 (45%)	19 (39%)	-	-
Multi	PySA	-	-	-	-	-	-	138 (55%)	34 (46%)
	CodeQL	55 (50%)	21 (36%)	63 (60%)	38 (56%)	88 (66%)	25 (51%)	120 (48%)	30 (41%)
	Joern	70 (63%)	17 (29%)	54 (51%)	13 (19%)	79 (59%)	18 (37%)	125 (50%)	25 (34%)
Ours	YASA	80 (72%)	32 (55%)	96 (91%)	45 (66%)	118 (88%)	35 (71%)	176 (70%)	44 (59%)
	Improvement	4~22%↑	14~26%↑	27%~40%↑	10~47%↑	22~64%↑	20%~40%↑	15~22%↑	13~25%↑

do not include Semgrep [57] because the community version of Semgrep does not support inter-procedural taint analysis.

4.2 RQ1: Detection Effectiveness

To evaluate YASA’s detection effectiveness, we compare its performance against six SOTA single-language tools and two multi-language frameworks on the xAST benchmark across four programming languages. Table 6 presents comprehensive results for both soundness cases and completeness cases.

Comparison with Single-Language Tools. YASA demonstrates superior performance compared to all single-language tools in both soundness and completeness. For Java, YASA passes 52 soundness cases and 40 completeness cases, compared to Tai-e’s 49 and 30, and Doop’s 38 and 31, respectively. Specifically, both Tai-e and Doop fail in field-sensitive analysis for arrays and maps, treating partial contamination as whole-object pollution, and struggle with path-sensitive scenarios where they conservatively merge execution paths rather than distinguishing feasible branches. In Go analysis, YASA passes 96 soundness cases and 45 completeness cases, significantly outperforming ARGOT, which passes 68 and 38 cases, respectively. ARGOT’s limitations include its conservative over-approximation, lack of automatic taint clearing on variable reassignment, and coarse control flow handling for defer statements and concurrency constructs. For JavaScript, YASA passes 118 soundness cases and 35 completeness cases, compared to ODGen’s 60 and 19, and DoubleX’s 32 and 15. DoubleX fails to support modern JavaScript features such as asynchronous programming, ES6+ syntax, and cross-module analysis. ODGen performs better but still struggles with advanced object-oriented features and modern constructs. In Python, YASA passes 176 soundness cases and 44 completeness cases, compared to PySA’s 138 and 34. PySA exhibits gaps in analyzing Python-specific features, including list comprehensions, generator functions, exception handling, and dynamic typing (e.g., aliasing and reflection mechanisms).

Comparison with Multi-Language Tools. YASA consistently outperforms both CodeQL and Joern across all languages in soundness and completeness. For CodeQL, the number of passed soundness cases ranges from 51 in Python to 88 in JavaScript, while

completeness cases range from 28 in Java to 37 in Go. These variations arise from CodeQL’s language-specific extractor architecture, where independent implementations for each language lead to inconsistent support. CodeQL struggles with context-sensitive analysis for Java parameter passing, field-sensitive analysis for JavaScript data structures, and Python-specific constructs such as list comprehensions and dynamic typing. Additionally, it fails to handle Go’s concurrency primitives, such as goroutines and channels, and nested struct analysis. Joern exhibits even greater inconsistencies, passing only 23 to 65 soundness cases and 11 to 22 completeness cases across languages. It struggles with polymorphism analysis, failing to effectively handle inheritance hierarchies, method overriding, and interface implementations. Joern also has significant gaps in field-sensitive analysis for multi-dimensional arrays, nested objects, and container types, often conflating partial contamination with whole-object pollution. The tool lacks support for modern language features, such as ES6+ constructs in JavaScript, Python generators and decorators, and Go’s concurrency mechanisms. Furthermore, Joern fails to perform cross-module analysis, making it unable to track taint flows across file and module boundaries, significantly limiting its utility for multi-language projects.

4.3 RQ2: Language Extensibility

To evaluate YASA’s language extensibility, we assess how effectively its unified design reduces engineering complexity when adding support for new programming languages. Our evaluation focuses on two key aspects: engineering efforts required to extend YASA to new languages, and the effectiveness of the language-agnostic semantic analyzer when applied without language-specific adjustments.

Engineering Effort to Support Each Language. We evaluate the reduction in engineering complexity achieved by YASA’s language-agnostic semantic analyzer by quantifying how much analysis logic can be shared across different programming languages. As shown in Table 7, the language-agnostic semantic analyzer handles an average of 77.3% of all semantic operations through 52 shared processing functions. These functions implement key analysis tasks such as variable resolution, expression evaluation, control flow analysis, and memory state management. This design ensures that language-specific analyzers only need to implement unique

Table 7: Semantic Rules Distribution Across Languages

Language	#Semantic Rules		Reuse Rate
	Agnostic	Specific	
JavaScript		19	73.2%
Python	52	15	77.6%
Java		10	83.9%
Go		18	74.3%
Average	-	15.5	77.3%

Table 8: Performance Contribution of Language-Agnostic vs. Language-Specific Semantic Analyzer

Language	Soundness		Completeness	
	Agnostic-only	YASA	Agnostic-only	YASA
Java	78 (2%↓)	80 (72%)	31 (2%↓)	32 (55%)
Go	80 (15%↓)	96 (91%)	41 (6%↓)	45 (66%)
JavaScript	107 (8%↓)	118 (88%)	33 (4%↓)	35 (71%)
Python	145 (12%↓)	176 (70%)	32 (16%↓)	44 (59%)

semantic characteristics rather than reimplementing core analysis algorithms. For instance, JavaScript requires 19 additional specialized semantic handlers, Python 15, Java 10, and Go 18, representing an incremental effort of only 16.1% to 26.8% across languages. We demonstrate that these shared semantics significantly reduce the engineering effort required to add support for new languages, validating the extensibility of its unified design.

Robustness of Language-Agnostic Analyzer. We assess the robustness of the language-agnostic semantic analyzer by evaluating its standalone performance across different programming languages without language-specific enhancements. This evaluation reveals how well language-agnostic semantic rules generalize across diverse programming paradigms. As shown in Table 8, when we evaluate using only the language-agnostic semantic analyzer (effectively disabling language-specific handlers), YASA still correctly solves a significant portion of test cases. It achieves a 77% success rate for JavaScript (140/183), 70% for Go (121/173), 65% for Java (109/169), and 54% for Python (177/326). This performance demonstrates that the language-agnostic semantic rules capture essential analysis patterns across languages. The results also highlight the crucial role of language-specific handlers, which increase overall benchmark success from 64% (547/851) to 74% (626/851).

4.4 RQ3: Real-world Practicality

To evaluate YASA’s practical effectiveness in real-world deployment scenarios, we conducted a large-scale study at Ant Group, focusing on both vulnerability discovery capabilities and scanning efficiency.

Vulnerability Discovery. We deployed YASA in production environments at Ant Group, scanning approximately 7.3K applications with over 100 million lines of multi-language code. The target systems span various web services, including frameworks like Egg.js, Flask, Spring, and Gin. As shown in Table 9, YASA identified 314 previously unknown vulnerability paths across 6 different vulnerability categories, including command injection, SQL injection, server-side

Table 9: Vulnerability Discovery at Ant Group

Language	Type	Reported	Sanitized	Conf.	Fixed
Python	CMDi	29	18	6	4
	CODEi	57	30	13	9
	SSRF	93	46	31	24
	Deserialization	3	/	3	2
Go	CMDi	7	5	2	2
	SQLi	28	19	9	9
	SSRF	29	17	11	10
JavaScript	HPE	55	36	12	11
	SSRF	13	8	5	5
Total	/	314	179	92	76

Table 10: Performance Evaluation of YASA on 80 Randomly Sampled Production Applications at Ant Group

Language	#Proj.	#LoC	Time (s)	Avg Time (s)	#KLoC/min
Java	20	3,945,483	4,548.1	227.4	52.1
Python	20	2,187,668	4,782.7	239.1	27.4
Go	20	1,432,519	2,372.2	118.6	36.2
JavaScript	20	561,946	3,650.2	182.5	9.2
Average	/	2,031,904	3,838.3	191.9	31.8

request forgery (SSRF), privilege escalation, and deserialization attacks. Security experts at Ant Group confirmed 92 of them (29.3%) as 0-day vulnerabilities, and 76 have already been fixed by the developers. As for the false positives, our manual verification reveals that 80.6% of unconfirmed taint paths (179 out of 222 false positives) were attributed to the sanitization mechanisms along the taint paths that YASA’s current implementation does not fully recognize.

Performance Efficiency. To evaluate YASA’s efficiency, we randomly sampled 20 applications for each supported language from the production environment. Table 10 details the performance metrics. YASA achieved an average scanning speed of 31.8 KLOC/min across the sampled dataset. Notably, Java analysis demonstrated the highest efficiency at 52.1 KLOC/min, benefiting from the robust type system and UAST optimization. Even for dynamic languages like Python (27.4 KLOC/min) and JavaScript (9.2 KLOC/min), the analysis time remains within acceptable limits for daily development workflows. These results confirm that YASA balances deep semantic analysis with the high-speed requirements in large-scale industrial deployment.

5 Discussion

Limitations. While YASA demonstrates significant advantages in multi-language taint analysis, several limitations warrant discussion. First, the UAST specification inherently reflects the characteristics of currently supported programming languages. As YASA evolves to support additional languages with fundamentally different paradigms, the UAST specification may require architectural refinements to accommodate novel semantic constructs. However, our evaluation demonstrates that the core universal abstractions remain stable across diverse programming paradigms, suggesting that future extensions will likely involve incremental enhancements.

rather than fundamental redesigns. Second, YASA’s language and framework coverage remains more limited compared to mature multi-language platforms like CodeQL and Joern. Currently, YASA supports 4 languages and 16 frameworks. This limitation primarily affects adoption in environments with diverse technology stacks that extend beyond YASA’s current scope. However, our evaluation demonstrates that adding new language and framework support requires significantly less engineering effort compared to building specialized analyzers, suggesting that coverage gaps can be addressed through community contributions. Third, YASA is not a fully sound framework; instead, we pursue soundness [41] and emphasize balancing performance in practical applications. This is primarily because, when handling loop structures, we typically adopt bounded unrolling rather than computing fixpoints. As a result, this approach may lead to missed vulnerabilities in scenarios involving complex control flows, such as deeply nested loops or recursive call patterns. Finally, YASA’s function call semantics modeling covers common built-in functions and popular third-party libraries, but defaults to conservative taint propagation for unknown functions. This approach assumes that any unknown function may propagate taint from input parameters to return values, which can lead to false positives in cases where functions perform sanitization or validation.

Future Work. Several promising research directions could significantly expand its impact and capabilities. First, YASA’s extensible architecture provides a natural foundation for supporting emerging programming languages (such as Rust, Ruby, ArkTS, etc.) and modern frameworks (React, Django, Vue, etc.) that exhibit unique computational semantics. Second, YASA’s unified multi-language representation opens opportunities for cross-language analysis that maintains semantic precision across language boundaries. Unlike traditional approaches that perform separate single-language analyses and subsequently bridge results through interface matching, YASA’s unified execution model can preserve calling context sensitivity and data flow relationships across multi-language applications. Third, YASA could benefit from incorporating classical techniques such as fixpoint computation and sparse value-flow analysis to improve its universal semantic computation processes, addressing both soundness limitations and computational efficiency challenges. Finally, we plan to develop a unified query language (QL) interface for YASA, which could enable declarative vulnerability rule specification and reduce migration barriers for organizations currently using CodeQL-based security workflows.

6 Related Work

Single-Language Static Taint Analysis Static taint analysis has been extensively studied for individual programming languages, with numerous specialized tools developed to address language-specific characteristics and security vulnerabilities. Java static analysis has achieved substantial maturity through tools like FlowDroid [4], Amandroid [69], and DroidSafe [23]. TAJ [65] focuses on Java web application analysis with techniques for handling reflective calls and container flows. Tai-e [63] represents a modern and user-friendly framework that harnesses designs from classic tools like Soot, WALA, and Doop. Memory safety challenges dominate

C/C++ analysis through tools like SVF [14, 62] for interprocedural sparse value-flow analysis and Pinpoint [58], which enables analysis of million-line codebases. JavaScript’s dynamic nature presents unique challenges addressed by specialized tools, including TAJJS [27, 32] for dynamic typing, DoubleX [20] for browser extension vulnerabilities, ODGen [31, 33, 34] for object dependency lookup and prototype pollution detection, and GraphJS [21] with multiversion dependency graphs for object state evolution. Existing Python analysis tools like PySA [19] and PyT [53] employ type inference as a foundation for subsequent taint analysis to handle Python’s dynamic typing and attribute access patterns. Recent work has explored LLM-assisted approaches, including LLMDFA [67] for compilation-free dataflow analysis, RepoAudit [25] for autonomous repository-level auditing, and Artemis [28] combining taint analysis with LLM assistance for SSRF detection. Despite these achievements, they exhibit fundamental limitations in multi-language environments, leading to significant engineering overhead.

Multi-Language Taint Analysis Several frameworks have emerged to address multi-language static analysis challenges. CodeQL [17, 22] provides a declarative query language over language-specific databases extracted through separate extractors, enabling cross-language queries but requiring substantial engineering effort for new language integration and facing semantic consistency challenges across language boundaries. Joern [8, 71] converts multiple languages into unified CPGs, but struggles with semantic precision for language-specific features and requires complex transformations for each language. WALA [55, 66] employs a common intermediate representation focused on JVM-based languages with extensions for dynamic languages, though its JVM-centric design limits effectiveness for fundamentally different execution models. Infer [18] focuses primarily on memory safety analysis for compiled languages like Java and C++ through separate frontends sharing abstract interpretation infrastructure, while Semgrep [57] offers fast pattern-based analysis through AST matching but with limited sophisticated dataflow analysis capabilities. Despite industrial adoption, these frameworks face limitations in designing intermediate representations that capture semantic richness across diverse programming languages.

7 Conclusion

In this paper, we presented YASA, a unified multi-language static taint analyzer. YASA introduces the UAST representation combined with point-to analysis to achieve high-precision taint analysis across multiple programming languages. Our comprehensive evaluation demonstrates that YASA consistently outperforms existing single-language and multi-language frameworks. The real-world deployment across 7,300 multi-language applications resulted in the discovery of 92 confirmed 0-day vulnerabilities, demonstrating YASA’s practical impact for industrial software security.

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