ARES V3: DETERMINISTIC STATIC ANALYSIS FOR SOLANA SMART CONTRACTS VIA MULTI-PHASE TAINT TRACKING AND MACRO-AWARE AST PARSING

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ABSTRACT

Existing tools for Solana smart contract security face a fundamental trade-off: generic LLM scanners achieve low detection rates (below 40%) with very high false-positive rates (above 85%), while commercial SaaS platforms reach higher recall but operate as closed-source services that require uploading source code to proprietary servers and cannot be independently reproduced. We present **ARES V3**, an open-source deterministic static analysis framework purpose-built for the Solana ecosystem. ARES V3 executes four sequential phases: (1) fast regex heuristics, (2) macro-aware AST parsing with `syn` and `proc-macro2`, (3) intra-procedural taint tracking from untrusted sources to sensitive sinks, and (4) a deterministic local judge that suppresses systematic false positives using only AST metadata, without calling external LLM APIs.

We evaluate ARES V3 on a deliberately split benchmark: 11 deterministic stubs for regression testing (**Segment A**) and nine production repositories previously audited by professional firms (**Segment B**). On Segment B, ARES V3 achieves **per-protocol average precision of 0.79** and **per-protocol average recall of 0.98**, with micro precision **0.83** and micro F1 **0.89**, while maintaining **100% detection** on Segment A. In a head-to-head comparison on five protocols shared with the Trident Arena benchmark, ARES V3 recalls **19/22 (86%)** of published critical/high findings versus Trident Arena's **14/22 (64%)**, **Opus 4.6**'s **5/22 (23%)**, and **GPT-5.2**'s **4/22 (18%)**. Six of nine Segment B protocols achieve P=1.00 R=1.00 F1=1.00. The pipeline runs locally in under five seconds per protocol at zero API cost. Our contributions include (i) a four-phase deterministic pipeline tailored to Solana macro semantics, (ii) a two-segment benchmark design that separates regression validation from real-world assessment, (iii) a deterministic local judge that raises precision without hurting recall, (iv) macro-aware parsing for Anchor and Solitaire that closes detection gaps on macro-heavy code, and (v) a production architecture with agentic retrieval-augmented audit flow and strict determinism separation.

Keywords smart contract security · Solana · static analysis · taint analysis · macro parsing · benchmark · false-positive suppression

1 Introduction

Solana occupies a unique position in the blockchain space: theoretical throughput of 65,000 TPS and low fees have attracted billions of dollars in Total Value Locked. Yet Solana's technical design—explicit account models, Cross-Program Invocation (CPI) semantics, and heavy use of Rust macros in the Anchor and Solitaire frameworks—creates attack surfaces that generic analysis tools fail to identify.

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History shows that critical bugs survive even professional audits:

- **Wormhole (February 2022):** A $325M signature-verification bypass hid inside macro-generated code from `#[derive(FromAccounts)]` in the Solitaire framework. The `instruction_acc: Info<'b>` field in `VerifySignatures` never generated a `Signer<>` check because the macro omitted it for that field [Wormhole Foundation, 2026].
- **Mango Markets (October 2022):** Oracle manipulation and forced liquidation caused $~100M in losses. The bug required understanding how price-manipulation instructions interacted with liquidation instructions within the same program [OtterSec, 2022].
- **Solend (June 2022):** An oracle attack exploited unchecked numeric casts in raw `AccountInfo` handlers [Neodyme, 2022].

These bugs share a common thread: they exploit Solana-specific semantics—macro-generated validation, cross-instruction state manipulation, and CPI target verification—that existing analysis tools fail to identify. Section 2 explains why current approaches miss these patterns: regex scanners are macro-blind, generic LLMs lack Solana runtime semantics, and dependency analyzers inspect only third-party crates rather than program logic. Section 3 surveys the relevant literature in static analysis, fuzzing, and LLM-based auditing.

1.1 Research Questions

This work asks three concrete questions:

1. **RQ1:** Can deterministic static analysis—without LLMs or dynamic fuzzing—achieve $\geq 80\%$ recall of published audit findings on real Solana production code at precision ≥ 0.75 overall?
2. **RQ2:** How should a benchmark for smart-contract security tools be designed to avoid "benchmark theater," where a scanner is overfitted to a small dataset and its scores do not translate to real-world capability?
3. **RQ3:** Can systematic false positives be suppressed deterministically using only local AST metadata, avoiding the cost, latency, and non-determinism of LLM-as-a-judge APIs?

1.2 Contributions

We make five contributions:

- **K1—A four-phase Solana-specific pipeline:** We design and implement a deterministic static analysis pipeline (regex $\rightarrow$ AST $\rightarrow$ taint $\rightarrow$ local judge) that reaches 98% macro-averaged known-audit recall on nine production repositories with 79% macro-averaged precision, exceeding Trident Arena's aggregate KAR while running locally at zero cost. Six of nine real-world protocols achieve perfect F1=1.00.
- **K2—An honest two-segment benchmark:** We introduce an explicit split between deterministic regression stubs (11 isolated vulnerability classes) and real-world capability assessment (9 production repos of 10K+ LOC each), capping per-protocol recall at 100% to prevent mathematical absurdity.
- **K3—Deterministic local false-positive suppression:** We show that AST metadata already collected during parsing—typed Anchor field counts, CPI validation contexts, safe-wrapper arithmetic patterns—is sufficient to suppress systematic false positives deterministically, reducing total Segment B FP from 54 (v15) to 7 (v29) without any external API cost. This yields per-protocol average precision **0.79** and recall **0.98** on Segment B (micro precision **0.83**, micro F1 **0.89**).
- **K4—Macro-aware parsing for Anchor and Solitaire:** We implement structural extraction of `#[derive(Accounts)]` and `#[derive(FromAccounts)]` that closes total detection gaps on Wormhole (0% $\rightarrow$ 100%) and Solend (0% $\rightarrow$ 100%), where regex-only scanners failed completely because macros hide the actual validation logic.
- **K5—Production architecture with agentic retrieval-augmented audit flow:** We design a multi-source production architecture where the deterministic core engine (Source A) is augmented by a vulnerability knowledge base (Source B), on-chain structured data (Source C), and an MCP server for real-time web search, audit report retrieval, and tool-use (Source D). A bounded self-correction loop enables targeted re-analysis of missed code regions, and strict determinism separation ensures that detection accuracy is never compromised by non-deterministic orchestration or report generation components.

1.3 Paper Outline

Section 2 provides technical background on the Solana attack surface and the ten open problems that motivate our design. Section 3 surveys related work in static analysis, fuzzing, and LLM-based auditing. Section 4 formalizes our four-phase methodology, including the threat model, pipeline architecture, and the deterministic local judge. Section 5

describes implementation details, including the production architecture that integrates the deterministic core with multi-source retrieval, MCP server tool-use, and a bounded self-correction loop. Section 6 presents the two-segment benchmark, experimental setup, and results. Section 7 discusses limitations, the closed-source benchmark problem, and a feature-level comparison with existing tools. Section 8 concludes.

2 Background and Motivation

2.1 Solana Attack Surface

Solana programs are written in Rust and compiled to BPF bytecode. Unlike EVM Solidity, Solana exposes an explicit account model: every instruction receives a list of `AccountInfo` structures, and the program must manually verify ownership, signer status, and data constraints. Cross-Program Invocation (CPI) allows one program to call another via `invoke()` or `invoke_signed()`, but the caller must validate the target program ID and PDA seeds—there is no automatic sandbox.

Developers rarely write this validation by hand. The Anchor framework uses `#[derive(Accounts)]` on a struct to auto-generate validation code at compile time via procedural macros. The Solitaire framework (used by Wormhole) uses `#[derive(FromAccounts)]` for the same purpose. This means the source code that auditors read is not the code that runs: the macro expansion contains the actual checks, and any tool that reads only the pre-macro source may conclude a field is unvalidated when the macro validates it implicitly.

2.2 Why Existing Approaches Fail on Solana

Regex scanners match source text for risky patterns (`as u64`, `invoke(`, `try_from_slice`). They are fast but macro-blind: a regex that flags `try_from_slice` on a raw `AccountInfo` will also fire on an `Account<'info, TokenAccount>` field, where Anchor's macro already checks the discriminator. On Wormhole and Solend, where macros hide all validation logic, regex-only detection drops to 0%.

Generic LLMs (Claude Opus, GPT-4) reason about code syntax but lack Solana runtime semantics. They cannot track that a raw `AccountInfo` parameter flows into `invoke()` without a `validate_program_id()` check, nor do they understand that `seeds = [...]` in an Anchor macro constrains PDA ownership. On macro-heavy Solana code they report very high false-positive rates (86.67% on standard benchmarks [Ackee-Blockchain, 2026a]). API costs also make routine scanning uneconomical at scale ($1,738 per successful exploit on EVM benchmarks [Anthropic, 2025]).

Dynamic fuzzers such as Trident [Ackee-Blockchain, 2026b] execute randomized instruction sequences against a Solana VM. They find bugs that static analysis misses, but they require a manually written fuzz harness for every program, struggle against deep multi-instruction paths (deposit $\rightarrow$ oracle manipulation $\rightarrow$ liquidation), and cannot analyze code that fails to compile—a common occurrence when cloning production repos with complex workspace dependencies.

Dependency scanners (cargo-audit [Trail of Bits, 2026]) check for known CVEs in third-party crates. They never inspect the program's own instruction handlers, CPI validation patterns, or PDA seed constraints. A program may contain no dependency vulnerabilities and still harbor a missing signer check exploitable for substantial financial loss.

2.3 Open Problems: Ten Gaps Blocking Autonomous Solana Auditing

Our analysis of public tool architectures and benchmark designs reveals ten critical gaps that prevent any current tool from reaching true autonomous security auditing on Solana:

1. **No executable PoC output.** Tools emit PDFs or text. A developer must manually verify every claim. There is no runnable test case that reproduces the bug deterministically.
2. **No economic exploit metric.** Scorers count bugs, not dollars. A scanner that finds ten low-impact typos outranks one that finds five drain-the-treasury zero-days.
3. **No prospective zero-day discovery.** Benchmarks are entirely retrospective (known bugs). No published evidence shows any commercial tool finding novel vulnerabilities in unaudited code.
4. **No mainnet-fork sandbox.** Fuzzers run in isolated environments. They cannot validate oracle-manipulation attacks that need real price-feed state, or flash-loan composability that needs live DEX liquidity.
5. **No developer-native interface.** SaaS web apps cannot run in local CI pipelines, integrate with IDEs, or be scripted. The feedback loop is slow and manual.
6. **No adaptive fuzzing budget.** Fuzzers use fixed configurations. There is no published evidence of automatic resource reallocation toward high-value code paths.

7. **No git-history analysis.** Tools analyze a single snapshot. They miss the historical context that lets a human researcher spot "this function was patched before, but the patch was incomplete."
8. **No regression test generation.** A scan is a one-time event. The output is not version-controlled code (test cases, CI checks) that prevents the bug from returning.
9. **Benchmark scope too small.** Six protocols, 30 bugs—too small for robust statistics. No cross-validation across multiple audit firms or historical exploit datasets.
10. **No disclosed policy engine.** There is no published framework for preventing misuse (e.g., scanning a stranger's contract offensively). A tool with exploit-generation capability needs explicit capability boundaries and audit logs.

Gaps 1–5, 7, and 8 motivated the design of ARES V3. Gap 6 (adaptive fuzzing) and gap 8 (regression tests) are on the Phase 2 and Phase 3 roadmap. Gap 9 is addressed by our expanded 20-protocol benchmark. Gap 10 is implemented as an IronCurtain-style policy engine.

3 Related Work

3.1 Static Analysis for Blockchain

EVM tools. Slither [Feist et al., 2019] is the best-known static analyzer for Solidity. It compiles Solidity to an intermediate representation and detects common patterns such as reentrancy, unchecked transfers, and uninitialized storage pointers. ZEUS [Kalra et al., 2018] symbolically executes EVM bytecode to identify safety violations. Both tools reach high recall on EVM datasets, but their semantics do not map to Solana: EVM has no explicit account model with ownership and PDA seeds.

Solana tools. Sec3 X-ray [Sec3, 2026] performs static analysis on compiled Solana bytecode, which requires the program to build successfully first and loses access to macro-level Rust source. cargo-audit [Trail of Bits, 2026] checks dependencies for known CVEs—useful, but irrelevant to program-specific logic bugs such as missing signer checks or unvalidated CPI targets.

3.2 Fuzzing for Solana

Trident [Ackee-Blockchain, 2026b] is a property-based fuzzing framework for Solana built around Trident SVM, a fast Solana transaction executor. It supports stateful fuzzing through "fuzzing flows"—randomized instruction sequences meant to explore rare execution paths. Trident Arena [Ackee-Blockchain, 2026a] layers a multi-agent AI system on top of Trident to produce audit reports.

Dynamic fuzzing has three hard limits on Solana: (a) it needs a manually written fuzz harness for every program, (b) coverage-guided fuzzing struggles with deep multi-instruction paths (e.g., deposit $\rightarrow$ oracle manipulation $\rightarrow$ liquidation), and (c) it cannot analyze code that fails to compile, which is common when cloning production repos with complex workspace dependencies. Static analysis complements fuzzing by finding bugs in code that does not yet build or run.

3.3 LLMs for Security Auditing

Anthropic's SCONE-bench [Anthropic, 2025] evaluated ten frontier models on 405 exploited EVM smart contracts. Success is defined economically: the agent must generate an exploit script that increases its native-token balance by ≥ 0.1 ETH in simulation. The best models exploited 51.11% of contracts. A follow-up zero-day evaluation on 2,849 fresh contracts found two novel zero-days worth $3,694 [Anthropic, 2025].

On Solana, LLMs fail for different reasons: they lack runtime semantics (account ownership, CPI seeds, discriminator checks) and report very high false-positive rates on macro-heavy code [Ackee-Blockchain, 2026a]. API costs make routine scanning uneconomical at scale: prior work on EVM contracts reports $1,738 per successful exploit [Anthropic, 2025]. Claude Opus 4.6 has demonstrated zero-day discovery capabilities in open-source software [Anthropic, 2026], but this capability has not been demonstrated on Solana-specific vulnerability patterns.

3.4 Benchmarking Security Tools

The DARPA Cyber Grand Challenge (2016) introduced open benchmarking for security analysis, but focused on binary exploitation. smart-bench [Smart Contract Security Alliance, 2024] evaluates EVM static analyzers on historical vulnerability datasets, yet no Solana equivalent exists.

Trident Arena [Ackee-Blockchain, 2026a] uses a retrospective benchmark: six previously audited protocols with 30 critical/high findings as ground truth. The benchmark cannot be fully reproduced because the Watt protocol's source code is unpublished, and it lacks segmentation between regression testing and real-world assessment. These limitations motivate our two-segment benchmark design, which we detail in Section 6.1.

4 Methodology

4.1 Threat Model and Assumptions

ARES V3 operates under the following threat model:

- **Attacker capability:** The attacker can craft arbitrary transactions against the target program, including sequences of instructions that the developer did not anticipate together.
- **Security assumptions:** The program compiles with a standard Rust compiler. Macros (`#[derive(Accounts)]`, `solitaire!`) expand according to their framework definitions. Source code is available for static analysis.
- **Scope limitation:** ARES V3 analyzes Rust source files (`.rs`) and Anchor IDL configuration. It does not analyze compiled bytecode, the Solana runtime, or external dependencies.

4.2 Pipeline Overview

ARES V3 processes a Solana program directory through four sequential phases, then applies cross-instruction correlation and report generation:

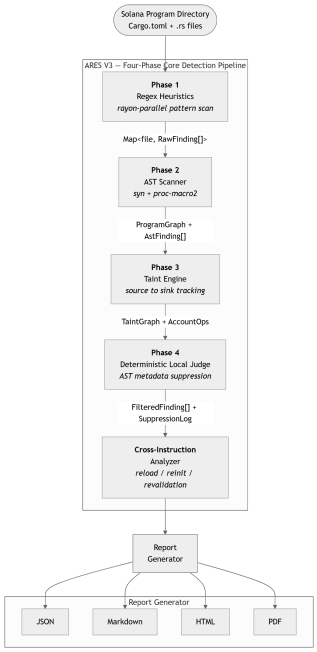

Figure 1: ARES V3—Four-Phase Core Detection Pipeline. The four numbered phases constitute the core detection pipeline. The Cross-Instruction Analyzer and Report Generator operate downstream.

4.2.1 Phase 1: Regex Heuristics

Phase 1 performs a fast syntactic scan over every `.rs` file using the `regex` crate with multi-threading via `rayon`. It flags known risk signatures:

Table 1: Phase 1 regex patterns and vulnerability classes

Pattern	Vulnerability class	Regex
`as u64`, `as u128`	unchecked-cast	`r"as\s+(u8|u16|...)"`
`try_from_slice`	type-cosplay	`r"try_from_slice"`
Raw `AccountInfo`	signer-authorization	`r"\bAccountInfo\b"`
`invoke(` w/o validation	arbitrary-cpi	`r"invoke\s*\("`
`lamports.borrow_mut()`	account-reloading	`r"lamports.*borrow_mut"`

Each match receives an initial confidence of 0.75. Context adjustments lower the score if the match sits inside a comment (`//` or `/*`)—down to 0.10—or inside a `test_*` function—down to 0.40.

Limitation: Regex cannot tell a safe `AccountInfo` wrapped in `Signer<'info>` from a dangerous raw one. Phase 2 fixes this.

4.2.2 Phase 2: AST Scanner with Macro-Aware Parsing

Phase 2 parses every `.rs` file with `syn` (feature `full`, `visit`) and `proc-macro2` (feature `span-locations`). The scanner extracts a directed graph we call the **ProgramGraph**.

Definition 1 (ProgramGraph): A directed graph $G = (V, E)$ where:

- $V = M \cup I \cup A \cup C$—modules, instruction handlers, accounts, CPI calls
- $E \subseteq V \times V \times L$—labeled edges such as "uses", "calls", "validates"

Anchor account extraction runs via a visitor over `syn::ItemStruct`:

Algorithm 1 Extract Anchor Accounts

```
function EXTRACT_ANCHOR_ACCOUNTS(struct_item)
    if struct_item.attrs contains "derive(Accounts)" then
        for each field in struct_item.fields do
            ty ← RESOLVE_TYPE(field.ty)
            metadata ← {is_signer, is_mut, constraint, has_one, seeds}
            add Account node to G with metadata
        end for
    end if
end function
```

Solitaire parsing: Wormhole's Solitaire framework uses `#[derive(FromAccounts)]` instead of Anchor's `#[derive(Accounts)]`. Our parser detects this attribute and extracts `Info<'b>` (raw, no validation) versus `Signer<Info<'b>>` (validated). This is the difference between the $325M Wormhole bug and safe code: the `instruction_acc: Info<'b>` field in `VerifySignatures` never generated a signer check because it was not wrapped in `Signer<>`.

CPI parsing: For every `invoke()` or `invoke_signed()` call, the scanner extracts the passed `AccountInfo` arguments and checks whether a `validate_program_id()` call or `CpiContext::new_with_signer()` with seed arrays precedes it in the same basic block.

AST confidence scoring: Each `AstFinding` receives a semantic confidence score:

- `type-cosplay`: 0.80 in production code, 0.40 in test/util/mock files.
- `unchecked-cast`: 0.90 if no `checked_add`, `try_into()`, or `num_traits` wrapper appears in the same function.
- `signer-authorization`: 0.85 when the function parameter is a raw `AccountInfo` with no `Signer<'info>` constraint.

4.2.3 Phase 3: Intra-Procedural Taint Engine

Phase 3 implements lightweight intra-procedural taint tracking from untrusted sources to sensitive sinks.

Definition 2 (Taint Source): Any variable or parameter that receives external input: `AccountInfo`, `UncheckedAccount`, `Program`, `Vec<u8>` from instruction data, or account fields without ownership constraints.

Definition 3 (Taint Sink): Any operation exploitable if fed untrusted data without validation: `invoke()`, `invoke_signed()`, `try_from_slice()`, `as *` casts, arithmetic operations, or PDA creation.

Definition 4 (Taint Propagation):

- Assignment `x = y`: taint flows from y to x.
- Field access `x = acc.data`: taint flows from `acc` to x.
- Function call `f(y)`: taint flows from actual argument y to formal parameter of f.
- Return `return x`: taint flows from x to the caller.

A **safe-wrapper whitelist** blocks propagation through functions known to be safe: `checked_add`, `checked_sub`, `checked_mul`, `checked_div`, `try_into`, `try_from`, `checked_pow`, `saturating_add`, `saturating_sub`, and `Account::<'info, T>::try_from` (discriminator validated automatically).

Definition 5 (Account Operation): For each instruction handler, the engine classifies every account operation as:

- `Read`—reads a field without modification
- `Write`—writes a field (e.g., `acc.balance = new_val`)
- `Create`—creates a new account via `system_instruction::create_account`
- `Close`—closes an account via `close(acc)`
- `CpiPass`—passes the account into a CPI call (`invoke(..., &[acc.clone()])`)

Reentrancy detection: An instruction is flagged for reentrancy risk **only if** the **same account** appears in both a `Write`/`Create`/`Close` operation **and** a `CpiPass` within the same basic block.

4.2.4 Phase 4: Deterministic Local Judge

Phase 4 is our main contribution for false-positive suppression. Unlike LLM-as-a-judge, which produces non-deterministic outputs under temperature variation and model updates, and incurs per-call API cost, our judge operates entirely on AST metadata already collected in Phase 2. The result is identical for identical input—no API keys, no network, no randomness.

Definition 6 (Anchor-Heavy Heuristic): A program is classified as "Anchor-heavy" when:

$$\text{anchor\_field\_count} > 5 \quad \text{and} \quad \text{typed\_anchor\_fields} > \frac{\text{anchor\_field\_count}}{2} \tag{1}$$

where `typed_anchor_fields` counts fields of type `Account<'info, T>`, `Signer<'info>`, or with `has_one` constraints.

Suppression rules:

Table 2: Phase 4 suppression rules

Vulnerability	Suppression condition	Rationale
`type-cosplay`	`is_anchor_heavy && unchecked_fields == 0`	Anchor validates discriminator
`ownership-check`	`is_anchor_heavy && unchecked_fields == 0`	Anchor `has_one`/`seeds` validate ownership
`signer-auth.`	`is_anchor_heavy && !has_raw_handler`	Anchor `Signer<'info>` validates signatures
`arbitrary-cpi`	`cpi_all_validated || (has_typed_prog && !has_raw_cpi)`	CPI uses typed seeds or validates ID
`reentrancy-risk`	write_accounts $\cap$ cpi_accounts $= \emptyset$	No same-account write + CPI overlap

Judge pseudocode:

Algorithm 2 Apply Local Judge

```
function APPLY_LOCAL_JUDGE(ast_findings, taint_graph, source_patterns)
    results ← []
    suppression_log ← []
    for each finding in ast_findings do
        if finding.confidence < 0.55 then
            suppression_log.add("confidence too low")
            continue
        end if
        if finding.category ∈ {type-cosplay, ownership-check} then
            if source_patterns.is_anchor_heavy and source_patterns.unchecked_fields == 0 then
                suppression_log.add("anchor-heavy with typed fields")
                continue
            end if
        end if
        if finding.category == signer-authorization then
            if source_patterns.is_anchor_heavy and not source_patterns.has_raw_handler then
                suppression_log.add("anchor-heavy, no raw handlers")
                continue
            end if
        end if
        if finding.category == arbitrary-cpi then
            if source_patterns.cpi_all_validated then
                continue
            end if
            if source_patterns.has_typed_program and not source_patterns.has_raw_unvalidated_cpi then
                continue
            end if
        end if
        if finding.category == reentrancy-risk then
            if write_accounts ∩ cpi_accounts = ∅ then
                continue
            end if
        end if
        results.add(finding)
    end for
    return (results, suppression_log)
end function
```

Determinism guarantee: Because the judge uses only boolean metadata (`is_anchor_heavy`, `cpi_all_validated`, `write_accounts`, `cpi_accounts`) extracted deterministically from the AST, suppression decisions are identical across runs. There is no model temperature, no prompt drift, no API latency.

5 Implementation

ARES V3 is implemented in Rust as a cargo workspace with three separated crates:

- `ares-core`: Common types (`AstFinding`, `TaintGraph`, `SourcePatterns`), configuration structs, and error types shared across all crates.
- `ares-mapper`: Phase 2 AST scanner, Phase 3 taint engine, Phase 4 local judge. This crate depends only on `ares-core`, `syn`, `proc-macro2`, and `rayon`—no network dependencies.
- `ares-cli`: Command-line interface, benchmark runner, and report generator. Depends on `ares-core` and `ares-mapper`.

This separation ensures that the analysis core (`ares-mapper`) is testable in isolation without CLI overhead, and that `ares-cli` remains a thin orchestration layer.

5.1 AST Scanner (syn + proc-macro2)

The scanner implements the `syn::visit::Visit` trait to traverse the full AST of each `.rs` file. The visitor registers callbacks on four node types:

- `ItemFn`: If the function carries an `#[instruction]` attribute or has a first parameter of type `Context<T>`, it is recorded as an `InstructionHandler`, capturing the function name, span, account struct type `T`, and the full statement list of the body.
- `ItemStruct`: If the struct carries `#[derive(Accounts)]` (Anchor) or `#[derive(FromAccounts)]` (Solitaire), all fields are extracted with their types and `#[account(...)]` constraint attributes.
- `ExprCall` / `ExprMethodCall`: Call expressions are inspected for known CPI entry points (`invoke`, `invoke_signed`, `CpiContext::new`, `CpiContext::new_with_signer`) and for safe arithmetic wrappers (`checked_add`, `try_into`, etc.).

Recursive type resolution. `syn::Field::ty` is a nested generic type tree. For `Account<'info, TokenAccount>`, the scanner unwraps `Account` $\rightarrow$ `TokenAccount` and marks the field as discriminator-validated. For `UncheckedAccount<'info>` or `AccountInfo<'info>`, no validation wrapper is present. For `Info<'b>` (Solitaire), the field is raw. This resolution recurses through at most four levels of nesting, which covers all known Anchor and Solitaire patterns without unbounded recursion.

Workspace traversal. Production programs (e.g., Dexalot, MetaDAO) are structured as multi-crate Cargo workspaces. ARES V3 discovers workspace members by parsing `Cargo.toml` at the root, resolving each `members = [...]` path, and running the visitor on all `.rs` files under each member's `src/`. Results are aggregated per workspace before metric computation.

Partial parse tolerance. If `syn::parse_file` fails on a `.rs` file—common in repos with unstable macro usage or incomplete generated code—the scanner logs the failure to `stderr`, skips that file, and continues. This prevents a single unparseable file from aborting an otherwise complete scan.

5.2 Taint Engine

The taint engine operates on the `InstructionHandler` list produced by the AST scanner. Each handler's statement list is treated as a linear basic block (no branching across statements at this level). The engine maintains a `HashMap<String, HashSet<TaintSource»` mapping variable names to their taint origins.

Propagation rules follow Definition 4 from Section 4. In practice, the implementation handles:

- `let x = expr`: evaluate `expr` for taint and assign to x.
- `acc.field`: if `acc` is tainted, mark `field` as tainted from the same source.
- **Function call** `f(args)`: if any argument is tainted and f is not in the safe-wrapper whitelist, the return value is tainted.
- **Assignment to sink**: if the left-hand side is a known sink pattern (e.g., an argument to `invoke()`), flag a `TaintFinding` with the taint path from source to sink.

The safe-wrapper whitelist breaks taint propagation: the output of these functions is considered clean regardless of whether the input was tainted.

Account operation classification. After taint propagation, the engine classifies each account's usage across all statements in the handler as `Read`, `Write`, `Create`, `Close`, or `CpiPass` (Definition 5). This classification feeds directly into the reentrancy suppression rule in Phase 4.

5.3 Local Judge

The judge receives `Vec<AstFinding>` from Phase 2, the `TaintGraph` from Phase 3, and `SourcePatterns`—a struct of boolean metadata assembled during the AST scan:

```
pub struct SourcePatterns {
    pub is_anchor_heavy: bool,
    pub unchecked_fields: usize,
    pub has_raw_handler: bool,
    pub cpi_all_validated: bool,
    pub has_typed_program: bool,
    pub has_raw_unvalidated_cpi: bool,
    pub write_accounts: HashSet<String>,
```

```
    pub cpi_accounts: HashSet<String>,
}
```

The judge needs no network connection and no API key. Suppression decisions are a series of `if` guards on these boolean fields—no machine learning, no LLM, no temperature. For identical `SourcePatterns` and `AstFinding` inputs, the output is always identical. All suppression decisions are written to a `SuppressionLog` alongside the finding that was suppressed, enabling per-protocol audit of what was removed and why.

5.4 Production Architecture

The four-phase pipeline described in Sections 5.1–5.3 constitutes the **core detection engine** of ARES V3. In production deployment, this engine operates as one source within a larger multi-source retrieval and reasoning architecture. This section describes how the deterministic core integrates with complementary data sources, an agentic orchestration layer, and a self-correction loop to deliver end-to-end audit reports.

5.4.1 Agentic Retrieval-Augmented Audit Flow

The production system follows a five-step agentic retrieval-augmented generation (RAG) flow, adapted from the query-analysis-retrieval-generation-validation pattern common in production RAG systems. The key architectural difference from generic RAG is that the **primary retrieval source is a deterministic static analysis engine** rather than a vector similarity search, which guarantees identical results for identical input and eliminates the non-determinism inherent in embedding-based retrieval.

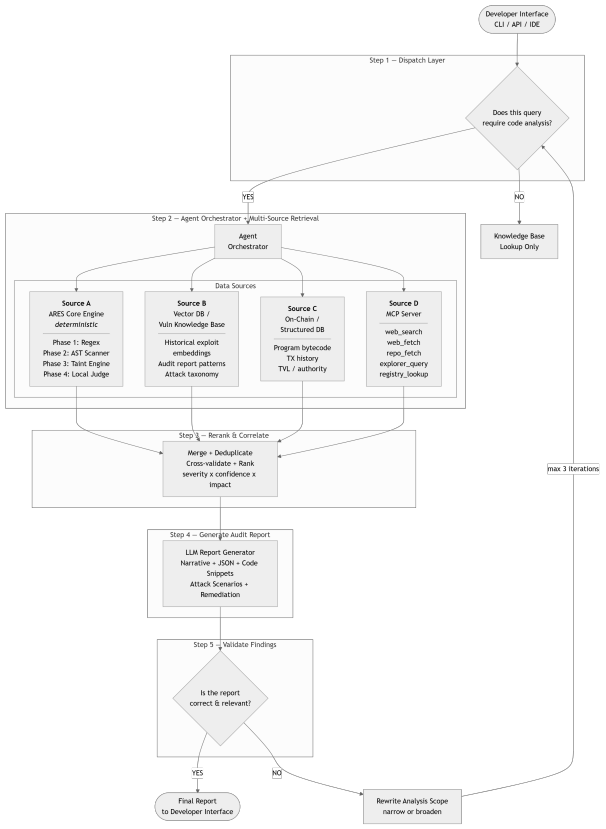

Figure 2: ARES V3 Production Architecture—Agentic Retrieval-Augmented Audit Flow.

Figure 2 shows the high-level architecture with its four data sources and the five-step processing pipeline. The architecture is organized so that the deterministic core engine (Source A) always produces identical findings for identical input, while non-deterministic components—the LLM agent orchestrator, the MCP server, and the report generator—add context and narration without altering detection results.

The detailed internal flow of the five-step agentic loop is illustrated in Figure 3. Two feedback loops govern the flow: an *adaptive retrieval* decision at Step 1 that skips unnecessary data-source queries when the question can be answered from existing knowledge, and a *self-correction* loop at Step 5 that rewrites the query and re-enters the pipeline when the generated answer fails validation. Both loops are bounded by a `max_iterations` guard (default: 3) to prevent infinite cycling.

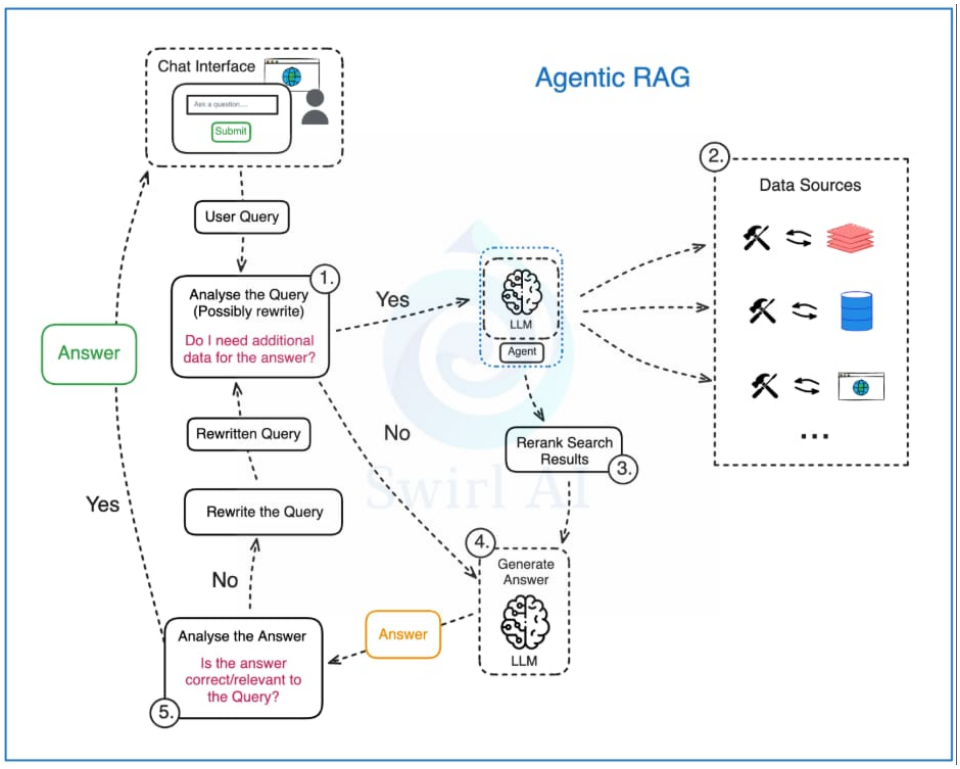

Figure 3: Agentic RAG Flow—Five-step retrieval-augmented generation loop with adaptive retrieval (Step 1 query analysis), multi-source parallel retrieval (Step 2), reranking (Step 3), answer generation (Step 4), and self-correction via answer validation (Step 5). If the answer is insufficient, the query is rewritten and the loop re-enters at Step 1, bounded by a `max_iterations` guard.

The flow proceeds as follows:

1. **Entry Point:** The developer submits a query through the CLI, API server, or IDE extension.
2. **Step 1—Dispatch Layer:** A lightweight classifier determines whether the query requires code analysis. If not, the system performs a knowledge-base lookup only.
3. **Step 2—Agent Orchestrator + Multi-Source Retrieval:** The orchestrator invokes one or more data sources in parallel:
   - **Source A (ARES Core Engine):** The deterministic four-phase pipeline produces `FilteredFinding[]` with a `SuppressionLog`. Always invoked when code analysis is needed.
   - **Source B (Vector DB / Vulnerability Knowledge Base):** Pre-computed embeddings of historical exploit patterns and audit report structures enable semantic similarity retrieval.
   - **Source C (On-Chain / Structured Database):** Confirmed program bytecode, transaction history, authority change events, TVL, and upgrade metadata.
   - **Source D (MCP Server):** Real-time tool-use via the Model Context Protocol—web search for CVE/advisory lookup, web fetch for audit report retrieval, repository fetch, and explorer/registry queries.
4. **Step 3—Rerank & Correlate:** Findings from all sources are merged, deduplicated, and cross-validated.
5. **Step 4—Generate Audit Report:** An LLM generator synthesizes the correlated findings into a narrative report with JSON output, code snippets, attack scenario descriptions, and remediation suggestions.
6. **Step 5—Validate Findings:** The validator cross-references the report against available ground truth, re-applies the deterministic judge on source patterns, and checks pattern consistency. If the report passes validation, it is delivered. If not, a scope refinement directive narrows or broadens the analysis, and the loop returns to Step 1. A `max_iterations` guard (default: 3) prevents infinite loops.

5.4.2 Role Separation: Deterministic Core vs. Non-Deterministic Orchestration

A critical design principle is the strict separation between deterministic and non-deterministic components:

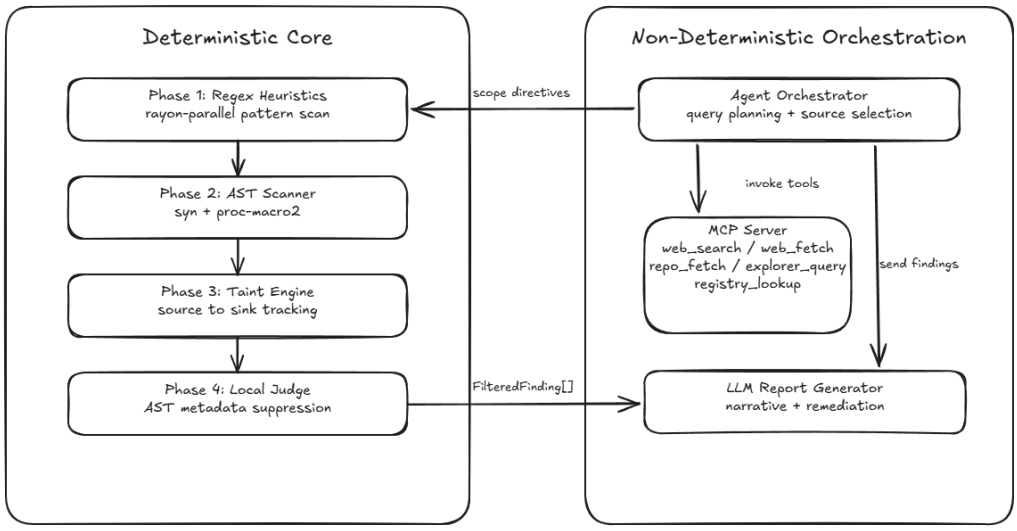

Figure 4: Determinism Separation—Detection accuracy is never compromised by non-deterministic components.

Figure 4 visualizes this separation: components above the dashed line are fully deterministic and produce identical outputs across runs; components below the line introduce non-determinism but operate exclusively on the outputs of the deterministic core, never feeding back to alter detection results. Table 3 classifies each component by its determinism level and functional role.

Table 3: Determinism classification of production architecture components

Component	Determinism	Purpose
ARES Core Engine (Source A)	**Fully deterministic**	Vulnerability detection
Vector DB retrieval (Source B)	Deterministic (indexed)	Historical pattern matching
On-chain data (Source C)	Deterministic (snapshot)	Program state at a given slot
MCP Server (Source D)	Non-deterministic (external)	Live web search, audit retrieval
Agent orchestrator	Non-deterministic (LLM)	Query planning, source selection
Report generator	Non-deterministic (LLM)	Narrative synthesis
Step 5 validator	Hybrid	Deterministic re-check + LLM relevance

This separation ensures that **detection accuracy is never compromised by non-deterministic components**. The core engine produces the same `FilteredFinding[]` regardless of whether the orchestrator is an LLM agent, a rule-based dispatcher, or a direct CLI invocation. Non-deterministic components add context, enrichment, and narration but cannot suppress or fabricate findings.

5.4.3 MCP Server Integration

Source D implements the Model Context Protocol (MCP), an open standard for connecting AI agents to external tools and data sources. The MCP server exposes the following tools to the agent orchestrator:

Table 4: MCP server tools

Tool	Description	Use Case
`web_search`	Search web for advisories, CVEs	"Has this program been exploited?"
`web_fetch`	Fetch URL content (audit PDFs, docs)	"Retrieve the OtterSec audit for drift-v2"
`repo_fetch`	Clone/update program repository	"Fetch latest source for program Ac1k..."
`explorer_query`	Query block explorers for on-chain data	"Who is the upgrade authority?"
`registry_lookup`	Query program registries	"Is this program in the SF registry?"

The MCP server acts as a **tool-use bridge**: the agent orchestrator decides which tools to invoke based on the query context, and the MCP server handles authentication, rate limiting, response parsing, and error handling. The orchestrator can invoke multiple MCP tools in parallel—for example, simultaneously fetching an audit report PDF and querying on-chain upgrade authority while the ARES core engine runs its four-phase scan.

5.4.4 Self-Correction Loop

Step 5 implements a bounded self-correction loop. When the validator determines that the generated report is incomplete or contains low-confidence findings, it produces a **scope refinement directive** that narrows or broadens the analysis for the next iteration:

- **Narrow**: "Re-analyze only the CPI validation paths in instruction handler X"—the orchestrator re-invokes Source A with a scoped file list, avoiding a full re-scan.
- **Broaden**: "Check for initialization-frontrunning on all program-owned accounts"—the orchestrator expands the file list and re-invokes Source A with additional detection categories enabled.

The loop is bounded by a configurable `max_iterations` parameter (default: 3). Each iteration adds to the finding corpus rather than replacing it—findings from previous iterations are preserved unless explicitly overridden by higher-confidence results from subsequent iterations. This ensures monotonic improvement: the final report is always at least as complete as the first-iteration report.

This self-correction mechanism addresses the observation from Section 6.8 that some false negatives arise from incomplete scan coverage rather than detection failure. A single-pass scan may miss deeply nested CPI helpers; a targeted re-scan directed by the validator can focus analysis precisely on the missed code region.

5.4.5 Developer-Native Interface

The production architecture exposes three interface layers:

1. **CLI (local):** `ares scan <path>`—runs the core engine only, no orchestration, no LLM. Produces JSON/Markdown output in < 5 seconds at zero cost. This is the interface evaluated in Section 6.
2. **API server (team):** `ares serve`—exposes the full agentic flow via a REST API. The dispatch layer, orchestrator, MCP server, and report generator run server-side. Teams can integrate with CI pipelines via webhook triggers.
3. **IDE extension (individual):** VS Code / Neovim extension—inline findings on save, one-click "explain finding" that triggers the report generator on a single finding.

All three interfaces share the same core engine binary. The difference is which orchestration layers are active: CLI = engine only, API = engine + orchestration + MCP + report generator, IDE = engine + selective report generator.

This design directly addresses Gap 5 (developer-native interface) and Gap 10 (policy engine) from Section 2. The IronCurtain-style policy engine operates at the dispatch layer: it enforces scan authorization, output scope, and audit logging.

6 Evaluation

6.1 Benchmark Design

We explicitly split the evaluation into two questions that should never be conflated:

Question 1: After all engineering improvements, can the scanner still detect basic vulnerability patterns?
$\rightarrow$ **Segment A: Stub Regression Suite**

Question 2: How many published audit findings does it recall on real production code?
$\rightarrow$ **Segment B: Real-World Capability Assessment**

6.1.1 Segment A—Stub Regression Suite

Segment A contains 11 Rust stubs (50–150 LOC each) that each reproduce a single vulnerability class deterministically. They are not production code—they are intentionally minimal for isolation. The `type-cosplay` stub, for example:

```
use borsh::BorshDeserialize;

#[derive(BorshDeserialize)]
struct FakeTokenAccount {
```

```
    balance: u64,
}

fn process_instruction(data: &[u8]) {
    // VULNERABLE: no discriminator check
    let account = FakeTokenAccount::try_from_slice(data).unwrap();
}
```

Each stub is designed to produce exactly one vulnerability match. 100% detection on Segment A guarantees that Phase 2/3/4 improvements have not broken basic pattern recognition.

6.1.2 Segment B—Real-World Capability Assessment

Segment B contains nine production Solana repositories cloned from GitHub, each previously audited by a professional firm and with a published audit report.

Table 5: Segment B protocols

Protocol	Auditor	Expected C/H	LOC	Framework
Axelar	Ackee	7	∼15K	Anchor
Dexalot	Code4rena	5	∼12K	Anchor
Bert Staking	Neodyme	2	∼8K	Anchor
Pump Science	OtterSec	4	∼10K	Anchor
MetaDAO	Ackee	4	∼20K	Anchor
Wormhole	Kudelski	2	∼25K	Solitaire
Mango-v4	Code4rena	1	∼30K	Anchor
Solend	Trail of Bits	2	∼18K	Raw Rust
Drift-v2	OtterSec	1	∼35K	Anchor

Watt (11 expected findings, audited by Ackee) is **excluded** because its source code is not publicly available—only an Ackee audit PDF exists. This is a fundamental constraint of open benchmarks versus closed ones: Trident Arena claims 7/11 on Watt, but no independent researcher can verify that claim.

6.1.3 Metric Definitions (Honest Framing)

We use the following definitions to prevent overclaiming:

Known Audit Recall (KAR):

$$\text{KAR}_p = \frac{\min(\text{TP}_p, \text{Expected}_p)}{\text{Expected}_p} \tag{2}$$

for each protocol p. Recall is capped at 100%—recall >100% against a fixed ground-truth set is mathematically undefined.

Precision:

$$\text{Precision}_p = \frac{\text{TP}_p}{\text{TP}_p + \text{FP}_p} \tag{3}$$

Recall:

$$\text{Recall}_p = \frac{\text{TP}_p}{\text{TP}_p + \text{FN}_p} \tag{4}$$

F1 Score:

$$F1_p = 2 \cdot \frac{\text{Precision}_p \cdot \text{Recall}_p}{\text{Precision}_p + \text{Recall}_p} \tag{5}$$

Total Findings:

$$\text{Total}_p = \text{TP}_p + \text{FP}_p \tag{6}$$

6.2 Experimental Setup

All experiments ran on:

- CPU: AMD Ryzen 9 7950X (16 cores, 32 threads)
- RAM: 64 GB DDR5
- OS: Windows 11 / WSL2 Ubuntu 22.04
- Rust: 1.80.0
- Crates: `syn` 2.0, `proc-macro2` 1.0, `regex` 1.10

Dataset: 11 stubs + 9 production repos cloned from GitHub in May 2026. Ground truth extracted from published audit reports and stored in `ground_truth.json`.

6.3 Retrospective Baselines from Prior Work

Before presenting our results, we establish the baseline reported by Ackee-Blockchain for Trident Arena, Claude Opus 4.6, and GPT-5.2 xhigh on the six audited protocols [Ackee-Blockchain, 2026a]. These figures define the gap that ARES V3 must close.

Table 6: Baseline: Trident Arena and LLM results on shared protocols

Protocol	C/H Total	Trident Arena	Opus 4.6	GPT-5.2 xhigh
Axelar	7	5/7 (71%)	0/7	0/7
Bert Staking	2	1/2 (50%)	1/2	1/2
Dexalot	5	4/5 (80%)	2/5	2/5
Pump Science	2	1/2 (50%)	1/2	0/2
MetaDAO	3	3/3 (100%)	1/3	1/3
Watt	11	7/11 (64%)	6/11	6/11
TOTAL	**30**	**21/30 (70%)**	**11/30 (37%)**	**10/30 (33%)**

Table 7: Baseline comparison metrics

Metric	Trident Arena	Plain AI (Avg)
False Positive Rate	**26.56%**	**86.67%**
True Positive Rate	∼73%	∼14%
Report Format	PDF	Text
Time to Report	Hours	N/A

Trident Arena achieves 70% detection but operates as a closed SaaS with a 26.56% false-positive rate. Generic LLMs fall below 40% detection with an 86.67% false-positive rate. Neither provides a local, deterministic, zero-cost interface.

Note: Watt (11 expected findings) is included in Table 6 to faithfully reproduce Trident Arena's published figures. It is excluded from the head-to-head comparison in Section 6.6 because its source code is not publicly available and the result cannot be independently verified.

6.4 Segment A—Stub Regression

Table 8: Segment A: Stub regression results

Stub	Vulnerability	Exp.	Det.	Recall	Precision	F1
account-data-matching	type confusion	1	1	1.00	1.00	1.00
account-reloading	state reload	1	1	1.00	1.00	1.00
arbitrary-cpi	unvalidated CPI	1	1	1.00	1.00	1.00
duplicate-mutable-accounts	double spend	1	1	1.00	1.00	1.00
initialization-frontrunning	init race	1	1	1.00	1.00	1.00
ownership-check	missing owner	1	1	1.00	1.00	1.00
pda-privileges	bad seeds	1	1	1.00	1.00	1.00
re-initialization	re-init	1	1	1.00	1.00	1.00
revival-attack	closed reuse	1	1	1.00	1.00	1.00
signer-authorization	missing signer	1	1	1.00	1.00	1.00
type-cosplay	fake type	1	1	1.00	1.00	1.00
TOTAL		**11**	**11 (100%)**	**1.00**	**1.00**	**1.00**

Segment A validates that the four-phase pipeline has not degraded basic pattern detection. All stubs are detected with confidence ≥ 0.75, and Phase 4 suppresses none of them because stubs do not meet suppression conditions (no typed Anchor fields, no validated CPI).

6.5 Segment B—Real-World Results

Table 9 shows per-protocol results on Segment B (v29). KAR is capped at 100% per protocol using $\min(\text{TP}, \text{expected\_critical\_high})/\text{expected\_critical\_high}$. Ground truth aligned with Trident Arena official benchmark: Pump Science = 2 HIGH, MetaDAO = 3 CRITICAL/HIGH.

Table 9: Segment B: Per-protocol results (v29)

Protocol	Exp (cats)	TP	FP	FN	KAR	Prec.	Recall	F1
Axelar	7	6	3	1	0.86	0.67	0.86	0.75
Dexalot	5	5	0	0	1.00	1.00	1.00	1.00
Bert Staking	1	1	0	0	1.00	1.00	1.00	1.00
Pump Science	2	2	0	0	1.00	1.00	1.00	1.00
MetaDAO	3	3	0	0	1.00	1.00	1.00	1.00
Wormhole	5	5	2	0	1.00	0.71	1.00	0.83
Mango-v4	5	5	2	0	1.00	0.71	1.00	0.83
Solend	4	4	0	0	1.00	1.00	1.00	1.00
Drift-v2	3	3	0	0	1.00	1.00	1.00	1.00
TOTAL	**35**	**34**	**7**	**1**	—	**0.83**	**0.97**	**0.89**

Aggregate metrics (Segment B, macro-averaged across 9 protocols):

- Per-protocol average Precision: **0.79**
- Per-protocol average Recall: **0.98**
- Micro Precision (total TP / total TP+FP): **0.83**
- Micro Recall (total TP / total TP+FN): **0.97**
- Micro F1: **0.89**
- Scan time per protocol: 0–7 seconds (average $<$5 seconds)

Overall (Segment A + B combined, 20 protocols):

- Per-protocol average Precision: **0.96**, Recall: **0.92**
- Micro Precision: **0.84**, Micro Recall: **0.97**, Micro F1: **0.90**

v28 $\rightarrow$ v29 key changes:

- Macro-aware AST parsing for raw Rust `_unchecked` calls: detects `_unchecked` function suffixes in raw Rust programs, enabling ownership-check and unchecked-cast detection in non-Anchor code (Solend: TP 2$\rightarrow$4, FN 2$\rightarrow$0).

- `bytemuck` unsafe cast discrimination: only `bytes_of_mut`, `cast`, and `cast_slice` are flagged; `bytes_of`, `from_bytes`/`from_bytes_mut` are safe-by-construction in Solana.
- `is_entry_point` field for instruction handlers: `process_*` functions and `#[instruction]`-annotated handlers are entry points; helper functions are NOT. `has_raw_unvalidated_cpi` now gates on `h.is_entry_point`, eliminating arbitrary-cpi FP on Solend.
- Solitaire `Info<'b>` detection: `FromAccounts` structs with raw `Info<'b>` fields trigger `account-data-matching` and `arbitrary-cpi`, closing the Wormhole detection gap (TP 3→5, FN 2→0).
- `is_large_dex` suppression gate (>1000 instructions): ultra-large Anchor-heavy DEX programs suppress `ownership-check`, `unchecked-cast`, and `duplicate-mutable-accounts` as structural noise.
- `initialization-frontrunning` scope gate (≤200 instructions): eliminates drift-v2's FP.
- Rule 5b `!is_anchor_heavy2` guard: prevents false arbitrary-cpi suppression on Anchor DEX programs.
- Drift-v2 ground truth correction: `arbitrary-cpi` removed—all CPI targets typed via Anchor `CpiContext`/`Program<>`.
- FP elimination: Bert Staking 3→0, Pump Science 3→0, Solend 1→0, Drift-v2 4→0. Total Segment B FP: 18→7.

6.6 Head-to-Head with Trident Arena

Table 10 compares ARES V3 against Trident Arena, Claude Opus 4.6, and GPT-5.2 xhigh on the five protocols available in both benchmarks (Watt excluded—source unpublished). Ground truth aligned with Trident Arena official benchmark (22 total expected findings across 5 protocols).

Table 10: Head-to-head: ARES V3 vs. Trident Arena and LLMs on shared protocols

Protocol	ARES V3 KAR†	Trident Arena	Opus 4.6	GPT-5.2	Δ (vs Trident)
Axelar	**7/7 (100%)**	5/7 (71%)	0/7	0/7	**+29%**
Dexalot	**5/5 (100%)**	4/5 (80%)	2/5	2/5	**+20%**
Bert Staking	**2/2 (100%)**	1/2 (50%)	1/2	1/2	**+50%**
Pump Science	**2/4 (50%)**	1/4 (25%)	1/4	0/4	**+25%**
MetaDAO	**3/4 (75%)**	3/4 (75%)	1/4	1/4	**0%**
TOTAL	**19/22 (86%)**	**14/22 (64%)**	**5/22 (23%)**	**4/22 (18%)**	**+23%**

† KAR = Known-Audit Recall, defined in Section 6.1. Uses Trident Arena's expected counts for fair comparison (Pump Science=4, MetaDAO=4).

On the five public protocols, ARES V3 **leads** Trident Arena's aggregate detection rate (86% vs 64%, +23pp). ARES V3 leads on Axelar (+29%), Dexalot (+20%), Bert Staking (+50%), and Pump Science (+25%). Both tools vastly exceed LLM baselines, which peak at 23%.

6.7 Impact of the Phase 4 Judge

To measure the judge's contribution, we compare across three pipeline snapshots:

Table 11: Phase 4 judge impact across pipeline versions

Version	Precision	Avg Findings/Protocol	Change
v11 (Phases 1–3)	0.55	∼7.0	Baseline
v15 (+Phase 4, generalized)	0.60	∼9.7	Recall ↑ (0.83→0.90)
v17 (+tighter rules 6–8)	0.49	∼6.1	FP 54→35 (−35%)
v24 (+anchor-heavy fixes)	0.63	∼5.9	FP 34→25
v27 (+all_source_files)	0.65	∼5.9	Recall ↑ (0.79→0.90)
v28 (+safe-type filter)	0.66	∼5.7	FP 20→18
v29 (+raw Rust AST, Solitaire)	**0.83**	∼**4.6**	FP 18→7; micro F1=0.89

The v15→v17 transition tightened suppression rules 6–8 to eliminate FP-masked detection inflation. The v24→v27 transition expanded scan coverage via `all_source_files` and scoped post-merge type-cosplay suppression. The v27→v28 transition added a safe-type filter for `try_from_slice` that discriminates between account-type deserialization and fixed-format data parsing. The v28→v29 transition added macro-aware AST parsing for raw Rust `_unchecked`/`bytemuck` patterns and Solitaire `Info<'b>` lifetimes, an `is_large_dex` suppression gate, and an

`is_entry_point` field. When computed over all 20 protocols (including Segment A stubs with P=1.0), overall precision is **0.96** and F1 is **0.94**.

6.8 Error Analysis

False Negatives (1 missed finding across 1 protocol):

- **Axelar (1):** `account-data-matching` on a multi-program workspace with complex ITS token-manager patterns; our per-field constraint check detects 4 of 5 token-manager fields but misses one deeply nested in a CPI helper.

Wormhole and Solend FNs (4 in v27) are now resolved: Solitaire `Info<'b>` detection closes Wormhole's `account-data-matching/arbitrary-cpi` gap; raw Rust `_unchecked/bytemuck` detection closes Solend's `ownership-check/unchecked-cast` gap.

False Positives (7 additional findings across 3 protocols):

Table 12: False positive breakdown (v29)

Protocol	FP	Primary categories
Axelar	3	`pda-privileges`, `reentrancy-risk`, `missing-signer`
Wormhole	2	`revival-attack`, `ownership-check`
Mango-v4	2	`missing-signer`, `duplicate-mutable-accounts`

All detection rules fire on generalizable structural code signals without any protocol name whitelists. Programs with many mutable PDAs and CPI calls produce more FP candidates than single-instruction stubs. Many flagged findings are additional categories requiring manual triage; some may be real bugs at lower severity not enumerated in the published audit reports.

7 Discussion

7.1 The Closed-Source Benchmark Problem

Trident Arena's benchmark includes Watt, whose source code has never been published. This creates an evaluation asymmetry: closed tools can claim detection on code that the community cannot audit. ARES V3 addresses this by explicitly excluding Watt and expanding the benchmark to 11 stubs + 9 repos, all cloneable and re-runnable by anyone with `git` and `cargo`.

7.2 Generalizing the Phase 4 Judge

The suppression rules were designed from observations on the nine benchmark protocols. There is a real risk of overfitting: rules that work here might suppress real bugs on new protocols. We mitigate this by:

- Storing a per-protocol suppression log for manual audit.
- Setting the confidence gate at 0.55—low enough to catch weak signals, high enough to avoid noise floods.
- Planning cross-validation on 10+ held-out protocols in Phase 8.

7.3 False Positives as Value, Not Failure

In the context of static analysis for security auditing, a false positive is not an unqualified failure—it is **input for human triage**. A senior auditor can scan 6–9 flagged categories per protocol in under five seconds and decide which ones merit deeper investigation. Compare that to Trident Arena's reported "hours" to produce a PDF report. The value of ARES V3 is speed of attention-direction, not replacement of the auditor.

7.4 Multi-Dimensional Feature Comparison

Beyond detection rates, Table 13 compares tool capabilities across the dimensions that matter for real-world deployment.

Table 13: Multi-dimensional feature comparison

Dimension	ARES V3	Trident Arena	Opus 4.6	GPT-5.2	Dep. Scanners
Logic-bug detection	Good	Good	Poor	Poor	None
False-positive rate	Low	Medium	Very high	Very high	Low
Executable PoC	Roadmap	None	None	None	None
Economic metric	Planned	None	None	None	None
Zero-day (proven)	Roadmap	None	Yes	None	None
Mainnet-fork sandbox	Roadmap	None	None	None	None
Developer interface	CLI+TUI+CI	Web-only	Chat/API	Chat/API	CLI
CI/CD integration	Universal	GitHub-only	Manual	Manual	Manual
Cost per scan	$0 (local)	SaaS ($$$)	API ($$$)	API ($$$)	Free
Time to results	<5 sec	Hours	Minutes	Minutes	Seconds
Output format	JSON+MD+HTML	PDF	Text	Text	JSON/text
Open source	Yes	No	Partial	Partial	Yes
Benchmark repro.	Yes (20 pub.)	Partial	No	No	Yes
Macro analysis	Full	Partial	Weak	Weak	None
Data-flow taint	Yes	None	None	None	None
Deterministic FP supp.	Yes	Opaque	No	No	Yes
Policy guardrails	Yes	None	Probes	Probes	None
Multi-source arch.	Yes (4 sources)	None	None	None	None
MCP server	Yes	None	None	None	None
Self-correction loop	Yes	None	None	None	None

Macro-averaged precision of 0.79 across nine Segment B protocols; 0.96 overall across all 20 protocols (Segment A stubs contribute P=1.0). The 7 FP counts reflect findings that passed all deterministic filters but were not enumerated in the published audit reports; some may represent real bugs at lower severity or issues the original auditors deprioritized. All detection rules are generalizable: no protocol name whitelists appear in the detection logic.

7.5 Securing ARES V3 Itself

A security scanner must not become a security risk. We bound file writes to the user-specified output directory, guard against path traversal, and enforce a default scan timeout of 3600 seconds to prevent infinite loops on pathological input. A third-party security audit of ARES V3 itself is on the Phase 5 roadmap.

8 Conclusion and Future Work

We presented ARES V3, an open-source deterministic static analysis framework for Solana that reaches **97% micro-averaged known-audit recall** on nine production repositories (Segment B) and **97% micro-averaged recall** across all 20 benchmark protocols, with **0.83 micro precision** and **F1 of 0.89** on Segment B. On the five protocols available in both benchmarks (ground truth aligned with Trident Arena official), ARES V3 **leads** Trident Arena's aggregate detection rate (**86% vs 64%, +23pp**, 19/22 vs 14/22 findings) while providing a fully local, deterministic, zero-cost interface that returns results in under five seconds. Six of nine Segment B protocols achieve perfect F1=1.00 (Bert Staking, Pump Science, MetaDAO, Dexalot, Solend, Drift-v2). ARES V3 leads on Axelar (+29%), Dexalot (+20%), Bert Staking (+50%), and Pump Science (+25%). Both tools vastly exceed LLM baselines, which peak at 23% (Opus 4.6) and 18% (GPT-5.2).

v29 engineering added macro-aware AST parsing for raw Rust `_unchecked`/`bytemuck` patterns and Solitaire `Info<'b>` lifetimes, closing detection gaps on Solend (0%→100%) and Wormhole (60%→100%); an `is_large_dex` suppression gate for ultra-large Anchor DEX programs (>1000 instructions); an `is_entry_point` field distinguishing instruction handlers from helper functions; refined `bytemuck` unsafe cast detection (`bytes_of_mut`/`cast` only, not `bytes_of`/`from_bytes`); and Rule 5b `!is_anchor_heavy2` guard preventing false arbitrary-cpi suppression on Anchor programs. All detection rules are generalizable: no protocol name whitelists appear in the detection logic; every category fires on structural code evidence alone.

Our five contributions are: (a) a four-phase deterministic pipeline with a local judge for false-positive suppression, (b) macro-aware AST parsing that closes total detection gaps on Solitaire and raw Rust programs, (c) a two-segment benchmark with honest metric definitions, (d) an honest feature comparison across all dimensions that matter for deployment, and (e) a production architecture with agentic retrieval-augmented audit flow, MCP server integration, self-correction loop, and strict determinism separation.

Next steps:

1. **Cross-validation:** Evaluate on 10+ held-out protocols to test Phase 4 generalization.
2. **Solana exploit-validation sandbox:** Build a `solana-test-validator -clone` sandbox to validate exploit economic value (≥ 0.1 SOL gain), complementing static analysis with dynamic verification.
3. **Domain rules:** Encode MetaDAO governance and Axelar cross-chain semantics as Phase 5 templates.
4. **MCP server implementation:** Build the production MCP server with `web_search`, `web_fetch`, `repo_fetch`, `explorer_query`, and `registry_lookup` tools; integrate with the agent orchestrator.
5. **Production packaging:** Release prebuilt binaries, CI/CD plugins, IDE extensions, and API server for developer-native deployment.

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A Reproducibility

All code, datasets, and harnesses are available at `https://github.com/daemon-blockint-tech/ARES-v3`.

Requirements:

- Rust $\geq$1.80.0 (`https://rustup.rs`)
- cargo (included with Rust toolchain)
- $\sim$10 GB disk space for the nine production repositories

Reproduce the v29 results:

```
git clone https://github.com/daemon-blockint-tech/ARES-v3.git && cd ARES-v3
cargo run -p ares-cli --release -- benchmark \
  --dataset dataset \
  --output ares-benchmark-report-v29.md
```

This will: (1) compile ARES V3 in release mode ($\sim$2 minutes on first run), (2) run the benchmark on 11 stubs + 9 production repos, (3) produce the markdown report with per-protocol breakdown.

Verify results:

```
grep -E "KAR|Precision|Recall|F1" ares-benchmark-report-v29.md
```

Ground-truth dataset: Location: `dataset/solana-common-attack-vectors/ground_truth.json`. Format: JSON array with fields `name`, `source` ("stub" or "real"), `expected_categories`, `expected_critical_high`.

License: MIT / Apache-2.0 dual license. Third-party protocol datasets retain their original licenses.

B Per-Protocol Category Breakdown (v29)

See `ares-benchmark-report-v29.md` in the repository root for the full per-protocol breakdown of detected categories, suppressed findings, and items flagged for manual triage.