SolQDebug: Debug Solidity Quickly for Interactive Immediacy in Smart Contract Development

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Abstract

Debugging Solidity contracts remains cumbersome and slow. Even a simple inspection, such as tracking a variable through a branch, requires full compilation, contract deployment, preparatory transactions, and step-by-step bytecode tracing. Existing tools operate only after execution and offer no support while code is under construction. We present SolQDebug, the first interactive, source-level assistant for Solidity developers that provides millisecond feedback before compilation or chain interaction. SolQDebug extends the Solidity grammar with interactive parsing, incrementally maintains a dynamic control-flow graph, and performs interval-based abstract interpretation guided by inline test annotations, enabling developers to simulate symbolic inputs and inspect contract behavior as in traditional debugging environments. In an evaluation on real-world functions, SolQDebug enables low-latency, statement-level analysis during development without requiring compilation or deployment.

Keywords: Smart Contract Development, Solidity, Debugging, Abstract Interpretation

1 Introduction

Smart contracts are the backbone of decentralized applications, and Solidity has become the dominant language for writing them (26?). As contracts grow more complex and control more assets, developers must reason about correctness throughout the development cycle—not just at deployment. Large language models (LLMs) such as **?**) or Llama (14) can assist with code generation but offer no guarantees of correctness. Ultimately, developers remain responsible for understanding variable interactions, control flow, and numeric boundaries during authoring.

Unfortunately, the debugging workflow for Solidity lags far behind traditional programming environments. Even a single inspection requires full compilation, deployment, transaction-based state setup, and manual bytecode-level tracing. Tools like Remix IDE (20), Hardhat (9), and Foundry Forge (5) replicate this costly pipeline, providing no live feedback during edits. A prior study found that 88.8% of Solidity developers described debugging as painful, and 69% attributed this to the absence of interactive, source-level tooling Zou et al. (40). Despite this widely acknowledged pain point, we find no existing research or tooling that provides interactive feedback during Solidity code authoring—a gap that this paper aims to fill.

This paper presents SolQDebug, a source-level interactive Solidity debugger powered by abstract interpretation. Rather than replacing runtime debuggers, it complements them by enabling symbolic, per-statement inspection during code authoring—before compilation or deployment. It targets the Solidity pattern of single-contract, single-transaction execution, where each function is isolated and stateless—ideal for static reasoning but difficult to simulate manually. To support this, SolQDebug applies interval-based abstract interpretation, which generalizes over symbolic inputs, exposes edge-case behaviors, and provides sound results with low overhead. This approach gives developers immediate feedback and enables them to reason efficiently about how symbolic inputs influence variable behavior. Although these inputs enable generalization across multiple cases, certain input configurations or control structures may lead to wider output ranges. We evaluate these behaviors empirically and propose annotation strategies that help maintain interpretability across typical Solidity patterns.

To achieve this goal, SolQDebug builds on two core ideas. First, it extends the Solidity grammar with interactive parsing rules and dynamically updates the control-flow graph to reflect incremental edits, enabling keystroke-level structural changes during code authoring. Second, it performs abstract interpretation seeded by inline annotations. These annotations, written directly in the source code, allow developers to specify symbolic values for both parameters and storage variables, similar to how traditional debuggers let users configure initial states and explore control flow.

We evaluate SolQDebug on real-world functions from Zheng et al. (38), demonstrating millisecond-scale responsiveness under symbolic input. Beyond latency, we analyze how input interval structure affects interpretability in common Solidity patterns, such as division-normalized arithmetic.

This paper makes the following contributions:

- We identify the main barriers to interactive Solidity debugging: latency from compilation, deployment, and transaction setup, and EVM constraints that prevent lightweight re-execution.
- We design an interactive parser and dynamic control-flow graph (CFG) engine that supports live structural updates and syntactic recovery.
- We introduce an abstract interpreter that incorporates developer annotations as symbolic input, supporting fast, deployment-free debugging workflows.

- We implement and evaluate SolQDebug on real-world contracts, demonstrating its millisecond responsiveness and exploring annotation strategies that maintain interpretability under a range of symbolic input patterns.

2 Background

2.1 Structure of Solidity Smart Contract

Solidity smart contracts may declare contracts, interfaces, and libraries. Executable business logic typically resides in contracts, and functions serve as transaction entry points. Variables are usefully grouped as global (EVM metadata such as msg.sender or block. timestamp), state (persistent storage owned by a contract), and local (scoped to a call). Types include fixed-width integers, address, booleans, byte arrays, and user-defined structs; containers include arrays and mappings. A mapping behaves like an associative array with an implicit zero value for unseen keys and is not directly iterable. Storage classes (storage, memory, calldata) indicate lifetime and mutability; we mention them only to fix terminology. Visibility and mutability qualifiers (public, external, internal, private; pure, view, payable) exist but are not central to our single-contract, single-transaction setting. Control flow (if/else, while/for/do-while, break/continue, return) follows C/Java conventions.

Listing 1: Minimal example used to illustrate grammar elements relevant to our analysis

```
contract Example {
    address public owner;
    uint256 public totalSupply = 1000;
    mapping(address => uint256) private balances;

    modifier onlyOwner() {
        require(msg.sender == owner, "not owner");
        _;
    }

    function burn(uint256 amount) public onlyOwner {
        uint256 bal = balances[msg.sender];
        uint256 delta;
        if (bal >= amount) {
            balances[msg.sender] = bal - amount;
            delta = amount;
        }
        else {
            delta = 0;
        }
        totalSupply -= delta;
    }
}
```

The example highlights the specific features we rely on later. State variables include general types (owner, totalSupply) and a mapping from addresses to balances; global variables appear implicitly in guards via msg.sender. The function burn introduces parameters and a local variable (bal). The modifier onlyOwner performs a precondition check before the function body executes; the placeholder underscore marks where the original body is inserted when the modifier is inlined. In analysis, such modifiers are expanded at their precise positions around the function body in the control-flow graph.

These grammar elements connect directly to our semantics. Guards such as require narrow feasible ranges along taken branches. Modifiers are inlined so that their precondition checks are analyzed in sequence with the function body. Containers like mappings remain symbolic until a concrete key is accessed, at which point an abstract value is materialized for that access. This level of detail suffices for our abstract interpretation in the single-contract, single-transaction scope without introducing parts of the language that our evaluation does not exercise.

2.2 Solidity Execution Model

To execute a Solidity contract on the blockchain, it must first be deployed. Deployment occurs through a one-time transaction that stores the compiled bytecode on-chain and invokes the constructor exactly once. After deployment, all subsequent interactions are message-call transactions. In these, the caller specifies a public function along with encoded calldata. Once the transaction is mined into a block, the Ethereum Virtual Machine (EVM) jumps to the designated entry point and executes the corresponding function sequentially. At runtime, Solidity variables fall into three distinct storage classes (26):

- **Global variables** represent implicit, read-only metadata provided by the EVM, such as `block.timestamp`, `msg.sender`, and `msg.value`.
- **State variables** store persistent data within the contract and retain their values across transactions.
- **Local variables** include function parameters and temporary values scoped to a single execution context.

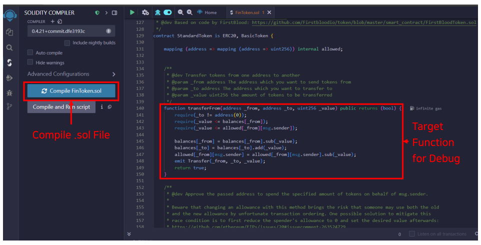
These three classes share a unified type system comprising primitive types like `uint` , `int`, `bool`, and `address`, as well as composite types such as arrays, mappings, and structs. Composite values can be nested to arbitrary depth using field access (`.`) or indexing (`[]`). Control flow follows familiar C-style constructs such as `if`/`else`, `while`, `for`, and `return`, alongside Solidity-specific statements like `emit` and `revert`.

As a result, debuggers must resolve potentially complex, multi-step expressions to analyze deeply nested elements within the contract state.

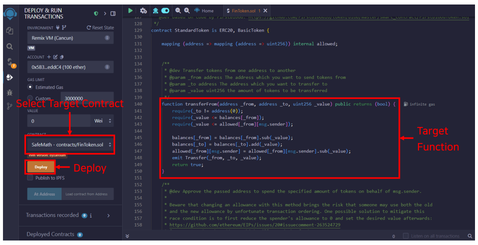
2.3 Root Causes of the Solidity-Debugging Bottleneck

Debugging Solidity programs remains significantly slower than traditional application development workflows due to two orthogonal obstacles.

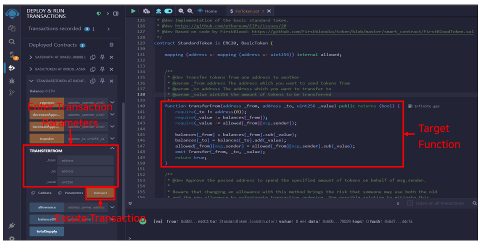
(1) Environmental disconnect. Unlike conventional IDEs such as PyCharm (11) or Visual Studio (17), where the source editor and execution engine run in the same process, Solidity development involves external coordination with a blockchain node at every stage of the workflow. Even a single debugging cycle must pass through four



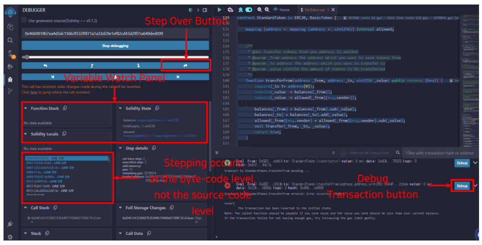
(a) Compile



(b) Deploy related contracts



(c) Send preparatory transactions



(d) Bytecode-level debugging

Fig. 1: Traditional Solidity debugging workflow

sequential stages (see Fig.1). First, the contract must be compiled. Then, the bytecode is deployed to a local or test chain. Next, developers must manually initialize the on-chain state by sending setup transactions. Finally, the target function is invoked, and its execution is traced step by step at the bytecode level.

This workflow introduces several seconds to minutes of latency per iteration, fundamentally breaking the fast "type-and-inspect" feedback cycle expected in modern development tools. To mitigate this friction, developers often rely on `emit` logs or event outputs to observe intermediate values. However, such instrumentation provides only runtime snapshots and lacks the structural insight needed to understand symbolic variation or control-flow behavior. Moreover, modifying the expression of interest typically requires recompilation and redeployment, compounding latency and disrupting iteration. The final stage—tracing raw EVM opcodes—is particularly costly, as developers are forced to mentally reconstruct source-level semantics. This not only adds execution overhead but also imposes significant cognitive burden during fault localization and fix validation.

(2) Architectural limitations of the EVM. The Ethereum Virtual Machine (EVM) is a state-based execution engine in which each transaction mutates a globally persistent storage. Once a function executes, its side effects are irreversible unless external intervention is performed. Re-executing the same function along the same control path is nontrivial: developers must either redeploy the entire contract to restore the initial state, or manually reconstruct the required preconditions via preparatory transactions—both of which incur significant overhead.

Additionally, if a function includes conditional guards that depend on the current state—such as account balances or counters—then any debugging session must first ensure that those conditions are satisfied. Fig. 2 illustrates this challenge: the debug target function enforces a check on `_balances[account]`, requiring developers to manually assign a sufficient balance before they can observe the downstream effects on `_totalSupply`. Without such setup, the function exits early, preventing inspection of the intended execution path.

In short, these constraints make repeated debugging iterations costly and fragile. According to a developer study (40), 88.8% of Solidity practitioners reported frustration with current debugging workflows, with 69% attributing this to the lack of interactive, state-aware tooling.

2.4 Proposed Methodology and Technical Challenges

SolQDebug addresses the two root causes of Solidity's debugging bottleneck—external latency from blockchain round trips, and internal opacity due to storage-based semantics—through a pair of lightweight but complementary techniques.

(1) Eliminating blockchain latency via in-editor interpretation. The traditional debugging workflow requires compilation, deployment, transaction-based state setup, and bytecode tracing—each incurring significant latency. SolQDebug replaces this round trip by performing both parsing and abstract interpretation directly inside the Solidity Editor. To support live editing, we extend the Solidity grammar with interactive parsing rules tailored for isolated statements, expressions, and control-flow blocks. When the developer types or edits code, only the affected region is reparsed using a reduced grammar.

Each parsed statement is inserted into a dynamic control-flow graph (CFG), and abstract interpretation resumes from the edit point. The interpreter uses an interval lattice, assigning each variable a conservative range $[l, h]$ to expose edge conditions (e.g., overflows or failing guards) and to approximate groups of concrete executions that follow the same path. This enables millisecond-scale feedback on code structure and control flow without compilation or chain interaction.

(2) Re-instantiating symbolic state without redeployment. The EVM does not support reverting to a prior state without redeploying the contract or replaying transactions—both of which disrupt iteration. SolQDebug introduces batch annotations as a lightweight mechanism for symbolic state injection. In essence, this reflects a core debugging activity: varying inputs or contract state to observe control-flow outcomes. Rather than reconstructing such conditions through live transactions, developers can write annotations at the top of the function to define initial abstract values. These values are injected before analysis begins and rolled back afterward, ensuring test-case isolation.

This approach brings the debugging workflow closer to the source by making state manipulation explicit and reproducible within the code itself. Developers can explore alternative execution paths by editing annotations alone—without modifying the contract logic or incurring compilation and deployment overhead. It effectively decouples symbolic input configuration from the analysis cycle, while preserving the intuitive debugging process developers already follow.

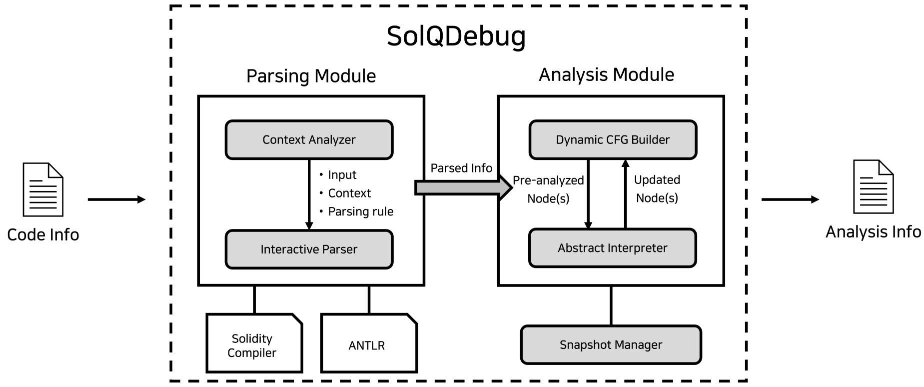


Fig. 2: SolQDebug architecture

3 The design of SolQDebug

SolQDebug processes code incrementally as developers write it, building up an abstract interpretation of the program. The system operates as follows. First, each incoming statement or annotation is interpreted under abstract semantics. Second, the corresponding construct is stored in a CFG node that is inserted at a semantically valid location, determined from the surrounding context and the existing control flow. Third, when batch debug annotations are present, the system reinterprets the function with the annotated values. The following subsections describe the architecture and core mechanisms that enable this incremental analysis.

3.1 System Architecture

The system accepts either single Solidity statements or batch debug annotations as input. These inputs are processed through two main modules:

(1) Parsing Module. Each incoming edit passes through the *Context Analyzer*, which extracts the surrounding source context needed to parse the partial statement or annotation. The *Interactive Parser*, built on **?**), applies an extended grammar that adds seven reduction rules to the standard Solidity grammar, enabling it to parse partial constructs that would normally fail to compile. Although the extended grammar can parse partial constructs, the system still validates the complete reconstructed source using the official Solidity compiler before proceeding to analysis. This validation ensures semantic consistency and rejects malformed input early.

(2) Analysis Module. The Analysis Module operates through three coordinated components. The *Dynamic CFG Builder* maintains an incremental control-flow graph that is updated as new statements are added: it creates corresponding nodes for each statement and rewires control edges to reflect the updated program structure. The *Abstract Interpreter* incrementally analyzes the updated CFG, reusing previous results and computing abstract values only for affected program points using a combination of interval and set domains. The *Snapshot Manager* ensures that each debug annotation execution starts from a clean state by preserving and restoring the abstract memory,

Table 1: Incremental inputs for the running example

Step	Lines of Input Fragment	Fragment
1	11--12	`function burn(uint256 amount) public onlyOwner {` `}`
2	12	`uint256 bal = balances[msg.sender];`
3	13	`uint256 delta;`
4	14--15	`if (bal >= amount) {` `}`
5	15	`balances[msg.sender] = bal - amount;`
6	16	`delta = amount;`
7	18--19	`else {` `}`
8	19	`delta = 0;`
9	21	`totalSupply -= delta; // new input`

allowing annotations to be modified and re-executed without side effects from previous runs.

(3) Line-Level Output. Following analysis, the system produces a per-statement summary showing the computed intervals for variables affected by each statement—including declarations, assignments, and return values. All outputs are mapped to their corresponding source line numbers and displayed inline within the editor, providing immediate feedback as developers write and modify code.

3.2 Running Example

To illustrate how the proposed architecture functions in practice, we present a concrete example using the `burn` function from Listing 1. This example demonstrates two key analysis modes: incremental edits (§3.2.1) and batch annotations (§3.2.2).

3.2.1 Incremental Source Code Analysis

As shown in Table 1, the developer incrementally constructs the `burn` function through nine distinct input steps, each introducing a new code fragment. SolQDebug accepts two kinds of fragments:

- **Block fragments** such as function headers or if/else blocks. When the developer types an opening '{', most editors auto-insert the closing '}', so the complete block arrives at once and may span multiple lines (e.g., Step 1 in lines 11–12 of Listing 1).
- **Single statements** ending with semicolons (e.g., Steps 2, 3, 5, 6, 8, and 9).

As the developer types each fragment, SolQDebug incrementally extends the CFG and recomputes abstract values only for affected program points. Figure 3 visualizes the CFG structure after Steps 1–8 have been integrated. We focus on Step 9 (`totalSupply -= delta;`), which illustrates how the system handles CFG insertion after a conditional branch merge. When Step 9 arrives, SolQDebug processes it as follows:

1. The interactive parser recognizes `totalSupply -= delta;` as an assignment.

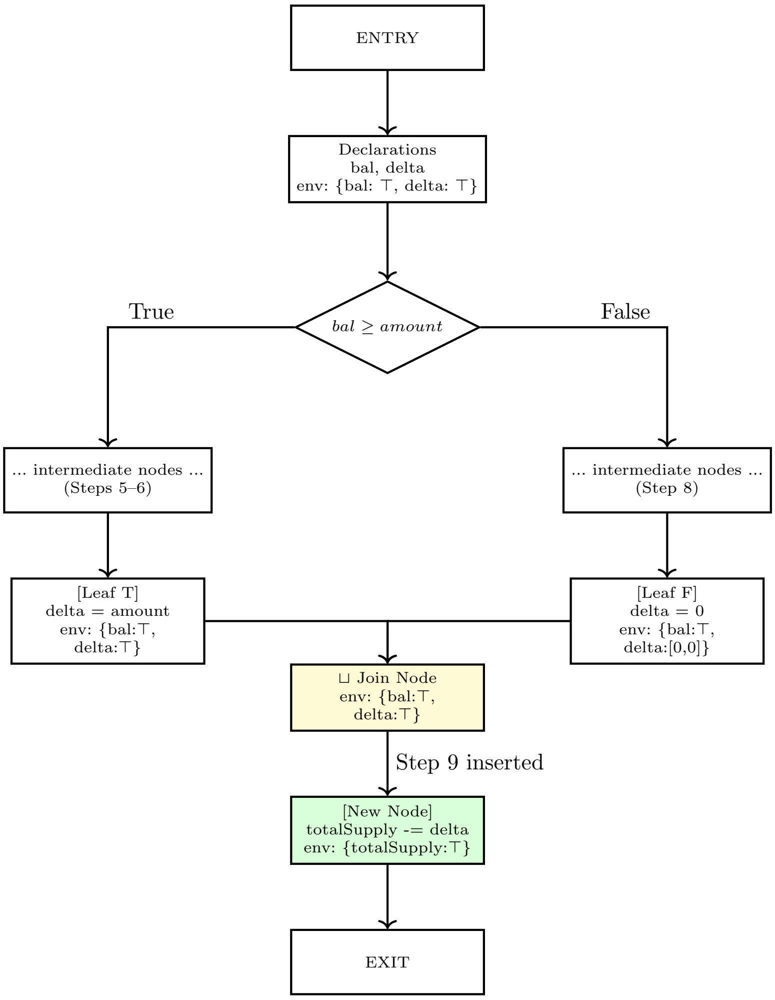


Fig. 3: CFG structure showing Step 9 insertion. Each statement occupies a separate basic node; intermediate nodes along each branch are omitted, showing only the leaf nodes before the join point. The join point node computes the least upper bound of environments from both branches

2. SolQDebug determines the insertion point by examining the edit context and existing CFG. In this case, the insertion point is after the join node that merges the if/else branches.
3. A new CFG node is created for the assignment, and edges are rewired: the join node now flows into this new node, which in turn connects to the exit.
4. The new node receives the environment from the join node, which holds the least upper bound ($\sqcup$) of environments from both branches.
5. SolQDebug reinterprets the new node and all reachable nodes to propagate the updated environment throughout the CFG.

This reinterpretation maintains soundness: it ensures that all affected nodes reflect the updated environment, allowing subsequent edits to directly reuse the computed abstract values without re-analyzing the entire program.

3.2.2 Batch Annotation Analysis

While incremental analysis supports the write-compile-debug cycle, developers often need to explore how different input ranges affect program behavior. This includes verifying price calculations in decentralized exchanges, balance constraints in token transfers, or liquidity ratios in automated market makers. Batch annotations enable this by letting developers specify initial states declaratively and obtain line-level results in a single analysis pass, reusing the CFG constructed during incremental edits.

Listing 2 shows the `burn` function with batch annotations. Annotation blocks are enclosed by `//@Debugging BEGIN` and `//@Debugging END`. Each annotation line specifies a variable type (`@StateVar` for state variables, `@LocalVar` for local variables) and assigns an interval value—supporting both simple variables and nested accesses like `balances[msg.sender]`.

Listing 2: Burn function with batch annotations

```
function burn(uint256 amount) public onlyOwner {
    // @Debugging BEGIN
    // @StateVar balances[msg.sender] = [100,200]
    // @LocalVar amount = [50,150]
    // @Debugging END
    uint256 bal = balances[msg.sender];
    uint256 delta;
    if (bal >= amount) {
        balances[msg.sender] = bal - amount;
        delta = amount;
    }
    else {
        delta = 0;
    }
    totalSupply -= delta;
}
```

In this example, we annotate `balances[msg.sender]` with the interval $[100, 200]$ and `amount` with $[50, 150]$ to explore how the `burn` function behaves under different balance and amount scenarios.

When a batch annotation block is encountered, SolQDebug follows a lightweight pipeline:

1. **Parse and validate.** Each annotation line is parsed, type-checked, and converted to the corresponding abstract domain (e.g., intervals for integers).
2. **Snapshot and overlay.** The current abstract memory is saved, and the annotated values are overlaid onto the initial environment.
3. **Single-pass analysis.** SolQDebug re-analyzes the pre-built CFG in a single pass using the annotated values as the initial environment.

Table 2: Interactive parser entry rules

Entry Rule	**Purpose**
interactiveSourceUnit	Top-level declarations: functions, contracts, interfaces, libraries, state variables, pragmas, imports
interactiveEnumUnit	Enum member items added after the enum shell is defined
interactiveStructUnit	Struct member declarations added after the struct shell is defined
interactiveBlockUnit	Statements and control-flow skeletons inside function bodies
interactiveDoWhileUnit	The while tail of a do-while loop
interactiveIfElseUnit	else or else-if branches following an if statement
interactiveCatchClauseUnit	catch clauses following a try statement

4. **Restore snapshot.** After analysis completes, the snapshot is restored to isolate successive annotation runs.

Unlike incremental analysis, batch annotations leave the CFG structure unchanged—only the initial environment differs. This makes batch runs lightweight, enabling rapid what-if exploration. Variables without annotations remain at $\top$, making explicit initialization essential for meaningful results. Formal details of the interactive parser and CFG construction appear in §3.3 and §3.4.

3.3 Interactive Parser

The Interactive Parser extends the Solidity language grammar **(author?)** (Solidity Language Grammar) with specialized entry rules that accept partial code fragments during incremental editing. The parser defines eight specialized entry rules: seven for partial Solidity constructs during incremental editing, and one for batch-annotation blocks that enable symbolic input scenarios.

Table 2 shows the seven rules, divided into two categories. *Primary rules* (`interactiveSourceUnit`, `interactiveBlockUnit`) handle independent constructs, while *continuation rules* complete partially-written structures by filling enum or struct shells or by appending control-flow branches. This separation prevents syntactically invalid constructs (e.g., an else-branch without a preceding if-statement) from being parsed as independent statements.

For concreteness, we refer to the burn function in Listing 1. The function header triggers `interactiveSourceUnit`, creating a function with an empty body. Each new statement invokes `interactiveBlockUnit`, which includes productions for both complete statements and control-flow skeletons (see Appendix A for the complete grammar hierarchy). For instance, typing `if (condition) {}` produces a skeletal if-statement. In the burn function, when the developer adds the `else` branch, `interactiveIfElseUnit` attaches it to the existing if-statement. This skeleton-based approach allows incremental construction, one construct at a time, without requiring syntactic completeness.

Beyond these seven interactive rules for Solidity constructs, the parser includes a specialized `debugUnit` rule for testing scenarios. The debugUnit rule parses batch-annotation lines that specify initial abstract values for variables, enabling symbolic input scenarios without contract deployment. The grammar defines three annotation types:

- GlobalVar assigns values to global variables such as msg.sender or block.timestamp
- StateVar assigns values to contract state variables, supporting nested access patterns like balances[msg.sender] or user.balance
- LocalVar assigns values to function parameters and local variables

Each annotation accepts an L-value and a value specification. Supported value formats include integer intervals, symbolic addresses, boolean values, and symbolic placeholders for bytes and strings. The parser validates type compatibility and range bounds at parse time, warning developers if annotated values are incompatible with declared types.

The annotation syntax and validation rules are specified in Appendix A, with the full ANTLR4 implementation available at **(author?)** (SolQDebug Language Grammar Rule).

3.4 Dynamic CFG Construction

Dynamic CFG construction maintains the control-flow graph incrementally as developers insert new statements. Rather than rebuilding from scratch, our approach modifies the graph in place. We proceed in three steps. First, we construct and splice a CFG fragment for each statement form. Second, we locate where to insert it in the existing graph. Third, we re-interpret only the affected region to update abstract environments.

Our CFG consists of the following node types:

- ENTRY NODE: The unique function entry point where execution begins.
- BASIC NODE: Holds exactly one statement (e.g., a variable declaration, an assignment, or a function call).
- CONDITION NODE: Represents branching constructs such as `if`, `else if`, `while`, `require`/`assert`, and `try`.
- JOIN NODE: Merges control flow from multiple branches (e.g., IF JOIN, ELSE-IF JOIN).
- FIXPOINT EVALUATION NODE (ϕ): The loop join point used for widening and narrowing during fixpoint computation.
- LOOP EXIT NODE: The false branch that exits a loop when the guard condition fails.
- RETURN NODE: A statement node whose outgoing edge is immediately rewired to the function's unique RETURN EXIT.
- ERROR EXIT: The function's unique exceptional exit (targets the exceptional path via `revert`, `require`, or `assert` failures).
- EXIT NODE: The function's unique normal exit point where execution terminates successfully.

3.4.1 Statement-Local, Incremental Construction

Every insertion operates at the CURRENT NODE without restructuring the rest of the graph. To enable direct insertion, each basic node holds exactly one statement. SolQDebug supports all Solidity statements; we present representative examples below.

Assignments, function calls, and unary operations create a single BASIC NODE inserted between the current node and its successors (Figure 4). An `if` statement creates a CONDITION NODE, true/false BASIC NODES, and an IF JOIN (Figure 5). An `else if` replaces the previous false branch with a new condition and its own join, connecting to the outer IF JOIN (Figure 6). An `else` attaches directly to the false branch without creating a new condition node (Figure 7).

A `while` loop creates a FIXPOINT EVALUATION NODE ϕ, a CONDITION NODE, a loop body node, and a LOOP EXIT NODE. The body connects back to ϕ for fixpoint iteration (Figure 8).

A `break` redirects its outgoing edge to the LOOP EXIT NODE (Figure 9). A `continue` redirects to the loop's ϕ node (Figure 10). A `return` is immediately rewired to the function's unique RETURN EXIT, detaching its original successors (Figure 11). A `require` statement creates a CONDITION NODE with the true edge connecting to a continuation node and the false edge pointing to the ERROR EXIT (Figure 12).

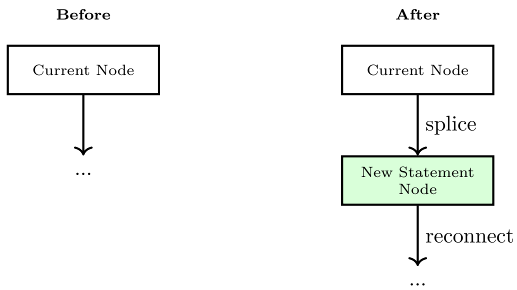


Fig. 4: Simple statement insertion. The builder creates one node and splices it between the current node and the original successors

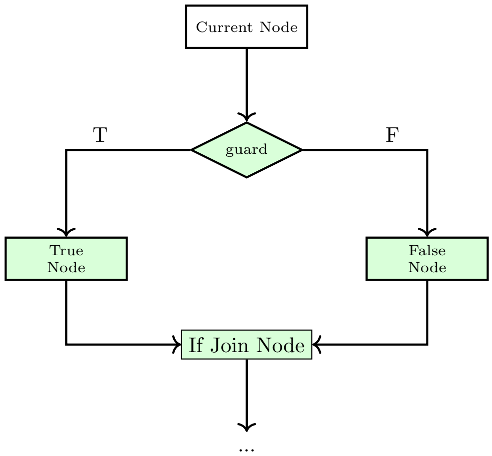


Fig. 5: If statement insertion. The builder creates a CONDITION NODE, two nodes for true/false arms, and an IF JOIN

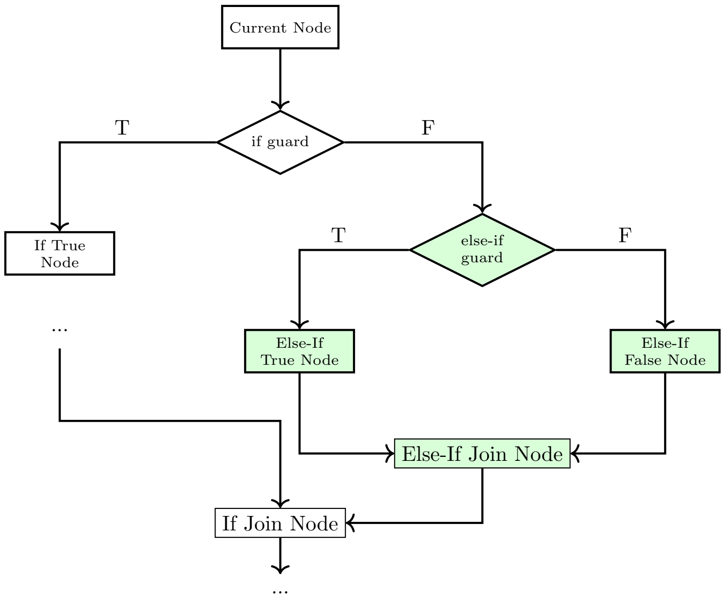


Fig. 6: Else-if statement insertion. The builder replaces the false arm with a new CONDITION NODE, two nodes, and an ELSE-IF JOIN

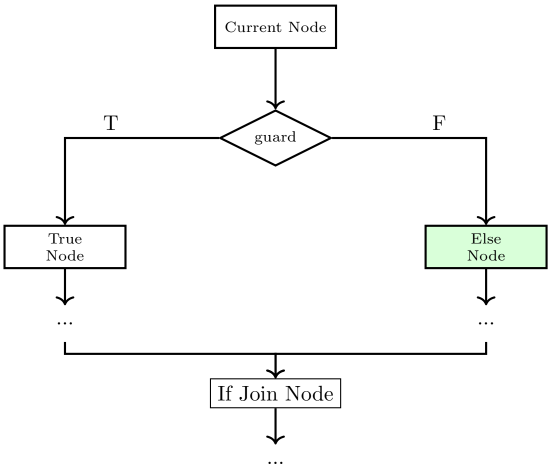


Fig. 7: Else statement insertion. The builder attaches a node to the false branch of the corresponding `if/else if`, connecting to the IF JOIN

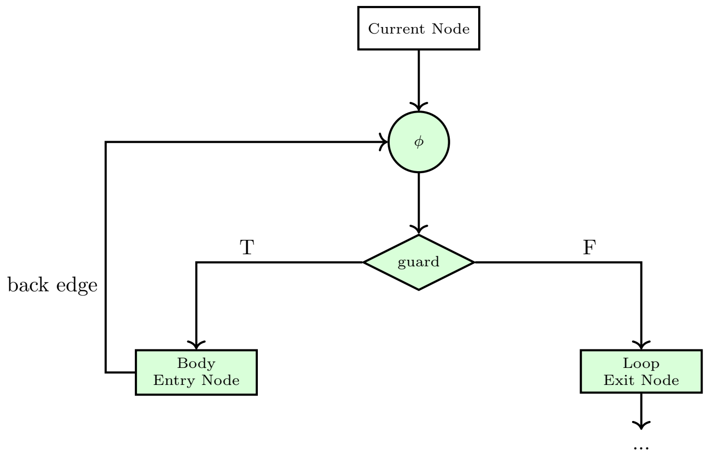


Fig. 8: While loop insertion. The builder creates a FIXPOINT EVALUATION NODE ϕ, a CONDITION NODE, a loop body node, and a LOOP EXIT NODE

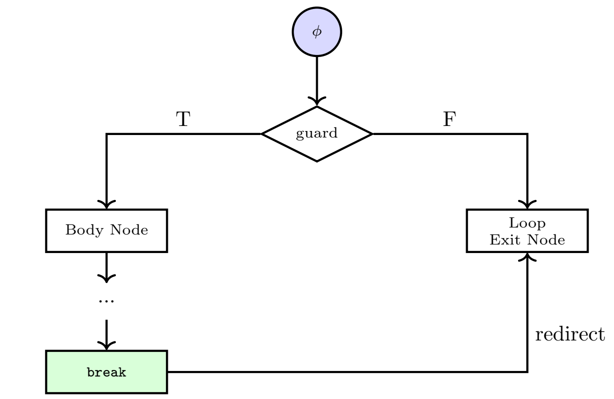


Fig. 9: Break statement insertion. The `break` node's outgoing edge is redirected to the LOOP EXIT NODE

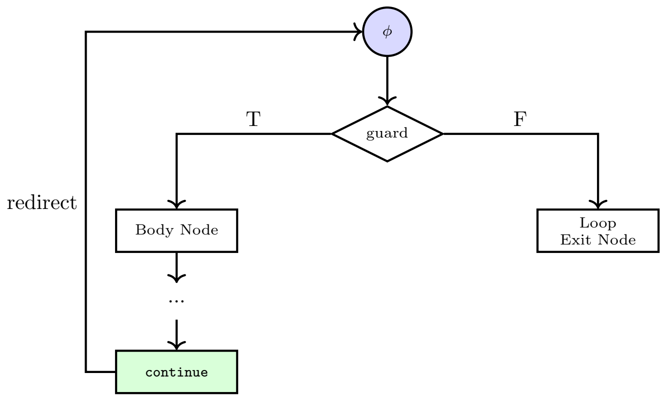


Fig. 10: Continue statement insertion. The `continue` node's outgoing edge is redirected to the loop's FIXPOINT EVALUATION NODE ϕ

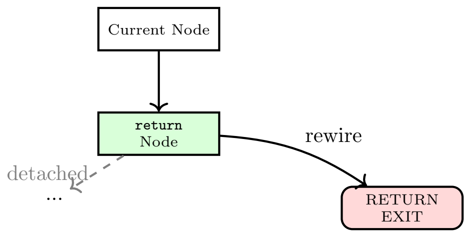


Fig. 11: Return statement insertion. The `return` node is rewired to the function's unique RETURN EXIT

Table 3: Line-to-node index mapping by statement type

Simple Statements			Compound Statements		
Statement	**Start Line**	**End Line**	**Statement**	**Start Line**	**End Line**
`Variable decl`	statement node	—	`if`	condition node	join node
`Assignment`	statement node	—	`else if`	condition node	join node
`break`	statement node	—	`else`	else node	join node
`continue`	statement node	—	`while`	condition node	exit node
`return`	statement node	—			
`require`	condition node	—			

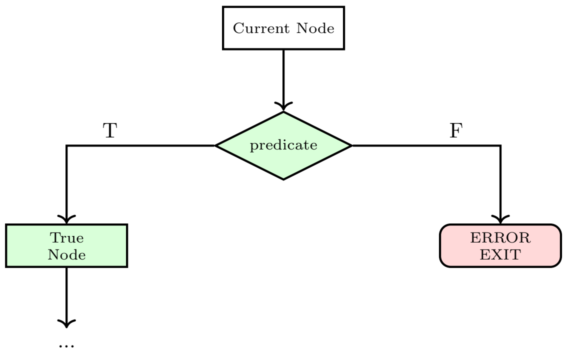


Fig. 12: Require statement insertion. The builder creates a CONDITION NODE with true edge to a node and false edge to the ERROR EXIT

These construction patterns enable SolQDebug to build the CFG incrementally as the user types each statement, without requiring the entire function body. The key challenge is determining *where* to insert each new node, which we address next.

3.4.2 Line-Based Insertion-Site Selection

Traditional CFG construction processes complete programs sequentially, building the entire graph in a single pass. In contrast, SolQDebug must handle partial code edits that specify only target line numbers. Since the CFG structure itself carries no line information, we cannot determine where an edit belongs without additional context. To enable line-based insertion-site selection, we maintain a line-to-node index during construction. Table 3 summarizes how statement types map lines to CFG nodes.

Simple statements index their start line only: most map to a statement node, while `require` maps to a condition node. Compound statements index both start and end lines: `if`/`else if`/`while` map their start line to a condition node and end line to a join/exit node, while `else` maps its start line to an else node and end line to the enclosing conditional's join node (see Figure 6 and Figure 7).

Algorithm 1 Dependent-Context Insertion

```
Require: CFG G = (V, E), edit context ctx ∈ {else_if, else}, current line L
Ensure: Condition node c ∈ V
1:  Queue ← FindJoinNode(L)                          ▷ find join node at or before line L
2:  if Queue = ∅ then
3:      error "No join node found at or before line L"
4:  end if
5:  Visited ← ∅
6:  while Queue ≠ ∅ do                                ▷ BFS through predecessors
7:      n ← Dequeue(Queue)
8:      if n ∈ Visited then continue
9:      end if
10:     Visited ← Visited ∪ {n}
11:     if isCond(n) and CondType(n) ∈ {if, else_if} then
12:         return n
13:     end if
14:     for p ∈ Predecessors(n) do
15:         if p ∉ Visited then
16:             Enqueue(Queue, p)
17:         end if
18:     end for
19: end while
20: error "No matching condition node found for context ctx"
```

This indexing scheme enables Algorithms 1 and 2 to locate insertion sites efficiently. We dispatch based on whether the statement can exist independently:

- `else`/`else if` **(dependent contexts):** Must attach to a preceding `if`/`else if` condition. Algorithm 1 traverses CFG predecessors to find the condition node.
- **All other statements (independent contexts):** Can exist independently. Algorithm 2 uses a successor-first strategy to find the insertion point.

Both algorithms never mutate the graph and rely solely on the line-to-node index for efficient lookup.

Algorithm 1: Dependent-Context Insertion. Dependent contexts (`else`/`else if`) cannot exist independently and must attach to a preceding `if`/`else if` condition node. The algorithm proceeds as follows:

- **Line 1–3 (initialization):** Retrieves CFG nodes at or before line L to initialize the BFS queue. These nodes include the join node of the preceding conditional, which serves as the starting point for backward traversal. If no nodes are found, the dependent context is invalid.
- **Line 5–13 (BFS traversal):** Performs BFS through CFG predecessors to find the matching condition node of type `if` or `else_if`. The BFS ensures we find the *nearest* enclosing condition.
- **Line 15:** Reports an error if no matching condition is found.

Algorithm 2 Independent-Context Insertion

Require: CFG $G = (V, E)$, edit span ending at line L
Ensure: Insertion-site node $A \in V$ (no graph mutation here)

```
1:  s ← FindPostNode(L)                              ▷ find first node after line L
2:  if isLoopExit(s) or isJoin(s) then               ▷ closing a loop or selection
3:      n ← FindPreviousNode(L)                      ▷ condition if exists, else last node
4:      if isCond(n) then
5:          return BranchBlock(n, true)              ▷ insert in TRUE branch
6:      else
7:          return n
8:      end if
9:  else                                             ▷ basic successor
10:     Pred ← Predecessors(s)
11:     if |Pred| = 1 then
12:         return the unique element of Pred
13:     else
14:         error "Basic successor must have exactly 1 predecessor"
15:     end if
16: end if
```

Algorithm 2: Independent-Context Insertion. For independent contexts (all statements except `else`/`else if`), we employ a successor-first strategy: by first identifying the post node (the next statement by line number), we determine the correct insertion point based on its CFG structure. This approach handles all statement types uniformly:

- **Line 1 (find post node):** FindPostNode(L) retrieves the first CFG node after line L.
- **Line 3–8 (loop-exit/join):** If the post node s is a loop-exit or join node, we search backward from L to find the previous node. FindPreviousNode(L) returns a condition node if present (loop header or `if`), otherwise the last node before L. If it is a condition node, we return its TRUE branch to place the new statement inside the construct; otherwise, we return the node itself.
- **Line 10–13 (basic post node):** Otherwise, s is a basic statement node. We retrieve its CFG predecessors and verify there is exactly one. Our CFG construction ensures this invariant (branches merge at join nodes, loops exit through loop-exit nodes); any other count indicates a malformed CFG.

3.4.3 Abstract Interpretation for Incremental Analysis

SolQDebug provides instant feedback on source code edits by propagating updates only along affected CFG paths, avoiding full re-analysis. When the user inserts statements, Algorithms 1 and 2 splice new nodes into the CFG, and incremental reinterpretation propagates updates from seed nodes marking insertion points. For debug annotations, SolQDebug performs full interpretation from the function entry node, ensuring all inspection points receive complete abstract states. Algorithm 3 performs incremental interpretation by propagating abstract states through a worklist-based dataflow analysis. When encountering loop headers, it delegates to Algorithm 4, which computes loop fixpoints using adaptive widening. The key innovation is EstimateIterations, which analyzes loop conditions to compute an adaptive threshold τ that defers widening. When debug annotations materialize concrete bounds (e.g., array lengths, parameter values), the analyzer infers tighter intervals for condition operands, raising τ to delay widening and preserve precision. Additionally, CondConverged detects early convergence by checking whether loop condition operands have stabilized to singleton intervals, allowing fixpoint computation to terminate before exhausting τ.

Algorithm 3 Incremental Interpretation

Require: CFG $G = (V, E)$; seed set S
Ensure: Environments updated along forward-reachable paths from S
1: $WL \leftarrow \langle\rangle$; $inQ \leftarrow \emptyset$; $Out \leftarrow$ snapshot map
2: **for all** $s \in S$ **do**
3:     **if** $\neg\mathsf{isSink}(s) \ \wedge \ s \notin inQ$ **then**
4:         $WL.\mathsf{enqueue}(s)$; $inQ \leftarrow inQ \cup \{s\}$
5:     **end if**
6: **end for**
7: **while** $WL \neq \langle\rangle$ **do**
8:     $n \leftarrow WL.\mathsf{pop}()$; $inQ \leftarrow inQ \setminus \{n\}$
9:     $\hat{\sigma}_{in} \leftarrow \bigsqcup_{p \in \textsc{Pred}(n)} \textsc{RefineByCondition}(p, n)$ ▷ join predecessors with path refinement
10:     **if** $\mathsf{isLoopHeader}(n)$ **then**
11:         $exit \leftarrow \textsc{Fixpoint}(n)$ ▷ compute loop fixpoint (Algorithm 4)
12:         $\textsc{EnqueueSuccessors}(exit, WL, inQ)$ **continue**
13:     **end if**
14:     $\hat{\sigma}_{out} \leftarrow \textsc{Transfer}(n, \hat{\sigma}_{in})$
15:     **if** $\hat{\sigma}_{out} \neq Out[n]$ **then**
16:         $(n) \leftarrow \hat{\sigma}_{out}$; $Out[n] \leftarrow \hat{\sigma}_{out}$
17:         $\textsc{EnqueueSuccessors}(n, WL, inQ)$
18:     **end if**
19: **end while**

Algorithm 3: Incremental Interpretation.

- **Line 1–5 (initialization):** Initialize worklist with seed nodes, filtering out sinks that contribute nothing to downstream analysis.
- **Line 7 (join predecessors):** Compute incoming environment by joining predecessors with path-sensitive refinement. Condition predecessors apply edge truth labels, pruning infeasible branches.
- **Line 9–11 (loop headers):** Invoke the loop fixpoint subroutine (Algorithm 4) to compute loop fixpoint, then enqueue the loop-exit successors for downstream propagation.

- **Line 13–17 (regular nodes):** Apply transfer function and change detection. Only when output changes do we enqueue successors, ensuring termination.

Algorithm 4 Loop Fixpoint with Adaptive Widening

Require: loop header node h
Ensure: Converged abstract environments for loop body and exit
1: $L \leftarrow \textsc{LoopNodes}(h)$; $\quad Start \leftarrow \bigsqcup\{(p) \mid p \in (h) \setminus L\}$
2: $\tau \leftarrow \textsc{EstimateIterations}(h, Start)$ ▷ annotation-aware threshold
3: $vis[\cdot] \leftarrow 0$
4: // **Widening phase**
5: $WL \leftarrow \langle h \rangle$; $\quad In[h] \leftarrow Start$
6: **while** $WL \neq \langle\rangle$ **do**
7: $\quad n \leftarrow WL.\mathsf{pop}()$; $\quad vis[n] \leftarrow vis[n] + 1$
8: $\quad \hat{o} \leftarrow \textsc{Transfer}(n, In[n])$
9: $\quad$ **if** $\mathsf{isJoin}(n) \wedge vis[n] > \tau$ **then**
10: $\quad\quad \hat{o} \leftarrow \textsc{Widen}(Out[n], \hat{o})$ ▷ widen after τ visits
11: $\quad$ **else**
12: $\quad\quad \hat{o} \leftarrow Out[n] \sqcup \hat{o}$
13: $\quad$ **end if**
14: $\quad$ **if** $\mathsf{isJoin}(n) \wedge \textsc{CondConverged}(n)$ **then break** ▷ early stop
15: $\quad$ **end if**
16: $\quad$ **if** $\hat{o} \neq Out[n]$ **then**
17: $\quad\quad Out[n] \leftarrow \hat{o}$; $\quad \textsc{PropagateToSuccessors}(n, L, WL)$
18: $\quad$ **end if**
19: **end while**
20: $\textsc{NarrowingPhase}(L)$ ▷ standard descending iteration
21: **return** Out

Algorithm 4: Loop Fixpoint with Adaptive Widening.

- **Line 1–3 (initialization):** Identify loop nodes, compute pre-loop environment, and estimate adaptive threshold τ by analyzing the loop condition. This is **annotation-aware**: when debug annotations materialize bounds (array lengths, parameters), tighter intervals raise τ and defer widening.
- **Line 6–15 (widening phase):** Iterate through loop nodes, applying widening only after τ visits at join nodes. Line 11 checks **early convergence**: when condition operands stabilize, the algorithm breaks before exhausting τ.
- **Line 17 (narrowing phase):** Apply standard narrowing (descending iteration with narrowing operator at join nodes) to refine the widened result.

Abstract Interpretation Framework. SolQDebug computes sound over-approximations of variable ranges using interval domains for integer types ($\widehat{\mathbb{Z}}_N, \widehat{\mathbb{U}}_N$), set abstractions for addresses and booleans, and on-demand materialization for composite types (arrays, mappings, structs). The complete formal semantics are in Appendix B.

4 Evaluation

To evaluate how SolQDebug performs in practical debugging scenarios, we organize our study around three research questions:

- **RQ1 – Responsiveness**: How much edit–to–inspect latency does SolQDebug eliminate compared to Remix?
- **RQ2 – Precision Sensitivity to Annotation Structure**: In a common Solidity pattern where inputs are normalized by division, how does the structure of operand intervals—overlapping vs. distinct—impact interval growth?
- **RQ3 – Loops**: Which loop structures lead to loss of precision, and how do symbolic inputs influence the stability of analysis?

4.1 Experimental Setup

We evaluate SolQDebug on a controlled local setup with the following hardware and software configuration:

- **CPU**: 11th Gen Intel® Core™ i7-11390H @ 3.40GHz
- **RAM**: 16.0 GB
- **Operating System**: Windows 10 (64-bit)
- **Implementation Language**: Python

The dataset is derived from DAppSCAN (38), a large-scale real-world benchmark for smart contract analysis comprising 3,345 Solidity files compiled with version `0.8.0` or higher. From this dataset, we selected 30 representative contracts using *complexity-driven stratified sampling* to ensure comprehensive coverage of debugging scenarios encountered in real-world Solidity development.

Our selection criteria focused on three dimensions that directly impact debugging complexity: (1) **computational complexity**— 10 contracts perform percentage/fee calculations with varying precision requirements (e.g., DapiServer computes update percentages with sign handling, GreenHouse distributes fees across 5 parties), 11 contracts implement time-based vesting or locking with multi-step calculations (e.g., Lock combines cliff periods with linear vesting, ThorusBond calculates claimable payouts from bond parameters), and several contracts perform accumulation with overflow protection; (2) **data structure complexity**—15 contracts use structs (averaging 4.5 fields, up to 9 in ATIDStaking), 10 contracts employ nested mappings (e.g., PercentageFeeModel uses 3-level override hierarchies, BitBookStake maps addresses to tiered fee structures), 8 contracts iterate over dynamic arrays, and multiple contracts combine mapping-to-struct patterns with conditional lookups; and (3) **control flow complexity**—8 contracts contain loops with varying termination conditions, many contracts use nested conditionals with early returns, and several employ modifier-based access control that affects variable scopes.

File Name	Function	Lines
AloeBlend.sol	`_earmarkSomeForMaintenance`	537-552
Amoss.sol	`_burn`	453-467
AOC_BEP.sol	`updateUserInfo`	422-436
ATIDStaking.sol	`_insertLockedStake`	127-172
AvatarArtMarketPlace.sol	`_removeFromTokens`	163-176
Balancer.sol	`_addActionBuilderAt`	79-91
BitBookStake.sol	`viewFeePercentage`	205-208
CitrusToken.sol	`transferFrom`	53-60
Claim.sol	`getCurrentClaimAmount`	65-72
Core.sol	`revokeStableMaster`	147-163
CoreVoting.sol	`quorums`	38-50
Dai.sol	`transferFrom`	72-83
DapiServer.sol	`calculateUpdateInPercentage`	838-854
DeltaNeutralPancakeWorker02.sol	`getReinvestPath`	392-405
Dripper.sol	`_availableFunds`	111-119
EdenToken.sol	`transferFrom`	227-240
GovStakingStorage.sol	`updateRewardMultiplier`	103-120
GreenHouse.sol	`_calculateFees`	328-344
HubPool.sol	`_allocateLpAndProtocolFees`	907-923
Lock.sol	`pending`	49-63
LockupContract.sol	`_getReleasedAmount`	75-89
Meter_flat.sol	`_transfer`	349-361
MockChainlinkOracle.sol	`latestRoundData`	114-130
OptimisticGrants.sol	`configureGrant`	62-79
PercentageFeeModel.sol	`getEarlyWithdrawFeeAmount`	72-95
PoolKeeper.sol	`keeperTip`	235-247
ThorusBond.sol	`claimablePayout`	531-538
ThorusLottery.sol	`isWinning`	708-714
TimeLockPool.sol	`getTotalDeposit`	90-96
WASTR.sol	`withdrawFrom`	211-232

Table 4: Benchmark dataset: 30 representative contracts from DAppSCAN with diverse debugging scenarios.

The 30 contracts range from 7 to 59 lines of code (average: 24 LOC), spanning fundamental DeFi patterns: token transfers with custom logic, staking/vesting mechanisms, liquidity pool operations, oracle data processing, and marketplace transactions. This diversity ensures coverage of key debugging scenarios—arithmetic precision, struct field tracking across updates, mapping traversal with multiple keys, accumulation in loops, and time-dependent state transitions—representing the challenges developers encounter when debugging real-world smart contracts. Table **??** lists all 30 benchmark contracts with their source files, target functions, and line ranges.

Since Remix IDE lacks built-in automated benchmarking capabilities, we developed `remix_benchmark`, a Selenium-based automation framework that programmatically drives the Remix web interface to measure edit-to-inspect latency. For each test

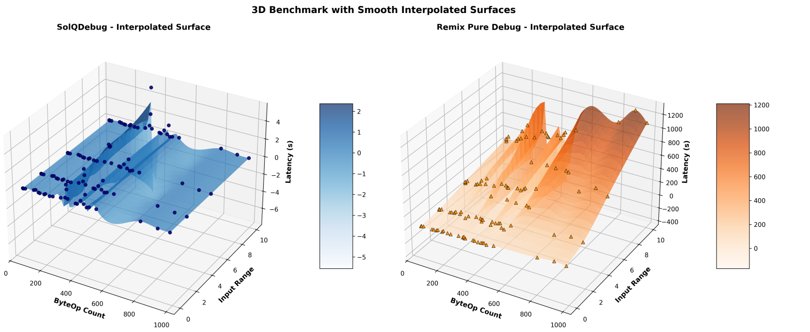


Fig. 13: Edit-to-inspect latency comparison between Remix and SolQDebug across varying test-case widths and execution passes. The x-axis represents the cost estimate, y-axis shows TestCase width (Δ), and z-axis displays latency in seconds. While Remix maintains constant high latency regardless of iteration, SolQDebug demonstrates significantly lower latency that quickly reaches a floor after the initial pass.

function, `remix_benchmark` automates the full workflow: compilation, contract deployment, state variable initialization via manual storage slot assignment, parameter entry, transaction execution, and step-through debugging. We measure two latency metrics: *pure debug time*, capturing only the debugger step-through duration, and *total time*, which includes compilation, deployment, and state setup overhead. The difference between these metrics reflects the additional manual effort required in traditional debugging workflows.

Although SolQDebug is designed for interactive use within a Solidity editor, all experiments simulate this behavior in a controlled scripting environment. For each function, we reconstruct a sequence of incremental edits and annotations that mimic realistic developer activity. These fragments are streamed into the interpreter to measure latency and interval growth under reproducible conditions.

4.2 RQ1 - Responsiveness

To evaluate responsiveness, we measure edit-to-inspect latency—defined as the time from a code change to the appearance of updated variable information—under a single contract, single transaction scenario.

We evaluated 30 functions across 4 test-case widths $\Delta \in \{0, 2, 5, 10\}$, yielding 120 total measurements for SolQDebug. For Remix, we measured each function once using `remix_benchmark`, capturing both pure debug time (debugger step-through only) and total time (including compilation, deployment, and state initialization).

For Remix, the pure debug time ranged from 25.1 to 124.6 seconds (median: 53.0 s), reflecting the time required to step through bytecode operations in the debugger. The total time, however, ranged from 71.1 to 168.3 seconds (median: 98.1 s), as it includes approximately 35 seconds for compilation and deployment, plus 0–11.8 seconds for manual state variable initialization (median: 2.9 s). Functions requiring more state

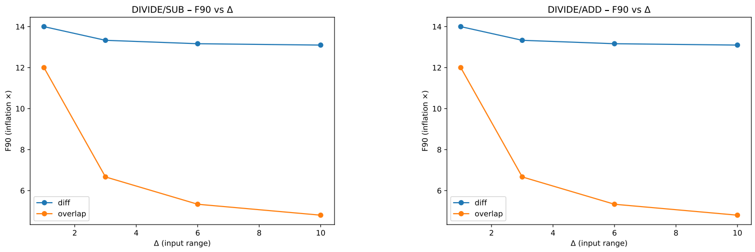


Fig. 14: Interval growth after normalization in `pending` function from `Lock.sol`. Left: original version with subtraction; right: modified version where subtraction is replaced with addition

slots incur proportionally higher setup overhead, with state initialization time growing linearly with the number of storage variables.

In contrast, SolQDebug completed analysis in 0.03–5.09 seconds (median: 0.15 s) across all 120 measurements, requiring no compilation, deployment, or state setup. Fig. 13 visualizes this performance gap: Remix pure debug time alone exceeds SolQDebug's total latency by a median factor of ˜350×, while total Remix latency (including setup) exceeds it by ˜650×. This demonstrates that SolQDebug eliminates the compile–deploy–setup cycle entirely, enabling immediate feedback during code editing.

Answer to RQ1: SolQDebug achieves sub-second edit-to-inspect latency (median: 0.15 s), eliminating 350×–650× overhead from Remix's compile–deploy–debug cycle. This enables immediate, interactive feedback during code editing without transaction execution.

4.3 RQ2 - Precision Sensitivity to Annotation Structure

Smart contracts often normalize raw inputs via division—e.g., converting timestamps to time units—before combining the results using addition or subtraction. To isolate the impact of the final arithmetic operator from the shared division step, we analyze two variants of the same control-flow structure: one using addition, the other using subtraction.

Each variant is tested under two annotation styles. In the diff style, each operand is assigned a distinct input interval (e.g., $[10, 20]$ and $[30, 40]$). In the overlap style, the intervals are partially aligned (e.g., $[10, 20]$ and $[15, 25]$), such that they share a subrange but are not fully identical. For each combination, we sweep the annotation width $\Delta \in \{1, 3, 6, 10\}$ and report F_{90}, the 90th percentile of the inflation factor $F = exit\_width/input\_width$.

Results in Fig.7 show that interval growth is more sensitive to the structure of input ranges than to the arithmetic operator. Diff inputs consistently trigger early widening as Δ increases, while overlap inputs maintain tighter bounds even under addition, which typically increases output range.

This suggests that in division-normalized logic, the alignment of operand intervals—whether disjoint or overlapping—has a stronger influence on interval growth than the choice between addition and subtraction. Overlapping inputs consistently result in smaller output ranges, reducing the degree of over-approximation as input width increases.

Answer to RQ2: In division-normalized arithmetic patterns, the structure of input interval annotations (overlapping vs. disjoint) has a stronger influence on precision than the choice of arithmetic operator (addition vs. subtraction). Overlapping intervals consistently reduce over-approximation by up to 3× compared to disjoint inputs, suggesting developers should align annotation ranges with expected input correlations to improve precision without sacrificing responsiveness.

4.4 RQ3 - Loops

Loop precision in SolQDebug depends critically on the evaluability of the loop condition expression. Recall from Algorithm 4 (line 2) that EstimateIterations analyzes the condition by evaluating both operands in the pre-loop environment *Start* to compute a widening threshold τ.

Table **??** summarizes the five loop-containing benchmarks analyzed in this study. We identify four distinct patterns based on these cases, each exhibiting different precision characteristics:

Contract	**Function**	**Loop Condition**	**Pattern**	**File**
AOC_BEP	`updateUserInfo`	`i <= 4`	1	`dataset/original/AOC_BEP.sol`
Balancer	`_addActionBuilderAt`	`i < additionalCount`	2	`dataset/original/Balancer.sol`
Core	`revokeStableMaster`	`i < length - 1`	2	`dataset/original/Core.sol`
TimeLockPool	`getTotalDeposit`	`i < array.length`	3	`dataset/original/TimeLockPool.sol`
AvatarArt...	`_removeFromTokens`	`i < tokenCount`	4	`dataset/original/AvatarArt...sol`

Table 5: Loop-containing benchmark contracts and their categorization. Pattern 1: constant-bounded with simple updates; Pattern 2: annotation-enabled convergence; Pattern 3: uninitialized local variables (developer fixable); Pattern 4: independent accumulation (inherent limitation).

Pattern 1: Constant-Bounded Loops with Simple Updates. When loop conditions reference only constants and the loop body contains only simple assignments (no accumulation), EstimateIterations computes precise thresholds without requiring annotations. For instance, `updateUserInfo` in AOC_BEP contains `for (uint256 i = 1; i <= 4; i++)`, where the condition `i <= 4` evaluates to $\tau = 4$. Inside the loop, variables are assigned directly (`level = i`), not accumulated. Because the actual loop iterates at most 4 times and contains no diverging operations, widening never triggers, and the interval for `userInfo[account].level` converges precisely to $[1, 4]$ without any annotations.

Pattern 2: Annotation-Enabled Convergence. When loop bounds depend on dynamic values (e.g., array lengths, computed variables) but the loop body contains only simple updates without problematic accumulation, debug annotations enable precise convergence. For example, `_addActionBuilderAt` in BALANCER uses `for (uint8 i = 0; i < additionalCount; i++)`, where `additionalCount` is computed from function inputs. When annotations specify the inputs (e.g., `index = 5`, `currentLength = 2`), the evaluator computes `additionalCount = 4`, yielding $\tau = 4$. Since the loop body only calls `actionBuilders.push()` without complex data-dependent logic, the analysis converges precisely. Similarly, `revokeStableMaster` in CORE iterates `for (uint256 i = 0; i < stablecoinListLength - 1; i++)` with simple index-based operations. Annotating the array length allows precise threshold computation, and the absence of problematic accumulation patterns ensures convergence.

Pattern 3: Uninitialized Local Variables (Developer-Fixable). Solidity does not automatically initialize local variables to zero. For instance, `getTotalDeposit` in TIMELOCKPOOL declares `uint256 total;` without initialization, then accumulates values via `total += depositsOf[_account][i].amount`. Since SOLQDEBUG conservatively models uninitialized variables as $\top$ (unknown), any arithmetic operation propagates $\top$, causing `total` to remain $\top = [0, 2^{256} - 1]$ regardless of array annotations.

This pattern represents a *developer-fixable* limitation: explicitly initializing `total = 0` would enable precise tracking. Debug annotations cannot compensate for missing initialization, as the interval domain soundly treats uninitialized reads as arbitrary values. Developers encountering this pattern should add explicit initialization.

Pattern 4: Independent Accumulation Variables (Inherent Limitation). Even when loop bounds are precisely known, variables that accumulate independently of the loop condition may still diverge under widening. `_removeFromTokens` in AVATARARTMARKETPLACE illustrates this: the loop iterates `for (uint tokenIndex = 0; tokenIndex < tokenCount; tokenIndex++)`, where `tokenCount` is known from array annotations. Inside the loop, `resultIndex` increments conditionally (`if (tokenItemId != tokenId) { resultIndex++; }`). Although the loop bound is finite, `resultIndex` depends on data values (how many elements match the condition), not the loop index itself.

After the widening threshold is exceeded, SOLQDEBUG conservatively widens `resultIndex` to $[0, \infty]$, as the interval domain cannot track the correlation between array contents and accumulator updates. This pattern is *inherent to the abstraction*: even perfect annotations of iteration bounds cannot prevent widening of variables whose updates depend on unpredictable data flow rather than iteration count alone. Developers should recognize that such accumulation patterns will exhibit conservative over-approximation.

Answer to RQ3: Loop precision in SolQDebug is governed by the adaptive widening threshold τ, which is computed by evaluating the loop condition in the pre-loop symbolic environment. We identify four patterns: (1) constant-bounded loops with simple updates converge precisely without annotations; (2) dynamic-bounded loops (e.g., iterating over array lengths) converge precisely when annotations provide sufficient information and the loop body lacks problematic accumulation; (3) uninitialized local variables propagate $\top$ regardless of annotations—developers must explicitly initialize such variables (e.g., `uint256 total = 0;`) to enable tracking; (4) accumulation variables whose updates depend on data values rather than loop indices (e.g., conditional increments) will widen to $[0, \infty]$ even when iteration bounds are known, as the interval domain cannot correlate array contents with accumulator state. Patterns 1-2 demonstrate annotation effectiveness, Pattern 3 is developer-fixable, and Pattern 4 represents an inherent abstraction limit.

5 Discussion

5.1 Why use Abstract Interpretation for Debugging

In this work, we use debugging to mean a developer-led, interactive exploration activity that happens before deployment during code authoring: the developer varies symbolic (interval) inputs and immediately observes branch reachability, guard validity, and value bounds at the source level. This edit-time feedback loop calls for a technique that (1) terminates quickly, (2) explains results in a way developers can inspect, and (3) scales to near-keystroke responsiveness.

We chose abstract interpretation (AI) over symbolic execution and proof-based verification for three reasons:

- **Termination.** AI enforces convergence via widening at loops and joins at merges, avoiding the path explosion common in symbolic execution.
- **Explainability.** Each result is an abstract value in a well-defined lattice. With interval domains, the mapping from inputs to outputs is explicit as ranges, which makes dataflow effects easy to trace and debug at the line level.
- **Responsiveness.** Interval transfer functions are lightweight, enabling millisecond-scale updates that fit the edit cycle. Symbolic engines routinely explore many paths even for small edits, which can break interactivity.

Formal verification provides stronger guarantees, but requires fully specified properties and invariants, which are costly to author during early iterations. SolQDebug is designed to bridge the gap between writing code and running tests or verification—offering immediate, sound, conservative feedback with low annotation overhead.

For debugging, intervals strike a practical balance between precision and speed. They (i) align with developers' mental model of "possible ranges," (ii) expose boundary effects (e.g., overflow thresholds, guard satisfaction regions) without committing to a single concrete input, and (iii) compose predictably through joins and widenings. In our setting, intervals are also a natural surface for annotations: developers can *shape* symbolic inputs (e.g., make them overlapping or disjoint) and directly see how that affects control flow and computed ranges.

AI's precision is conservative by design; edit-time usability depends on giving developers simple levers to steer precision without sacrificing responsiveness. We expose three such levers that proved effective in our study:

- **Annotation structure.** Overlapping operand intervals often bound output ranges more tightly than disjoint ones in division-normalized arithmetic (cf. RQ2). This reduces false alarms with no runtime cost.
- **Annotation width.** Narrower inputs shrink joins and delay widening; developers can start narrow and broaden gradually ("zoom out") to probe stability.
- **Guard-guided narrowing.** Making explicit the intended `require`/`if` guards in annotations tightens feasible states early and improves precision along the taken branch at negligible cost.

Where stricter precision is essential (e.g., inside data-driven loops), the workflow can temporarily fall back to concrete inputs for local inspection, then return to intervals for broader exploration. This "concrete when needed, symbolic by default" rhythm preserves interactivity while keeping results actionable.

5.2 Evaluation Implication

Traditional debuggers (e.g., Remix, Hardhat Debug) require compile–deploy–execute per iteration, typically taking tens of seconds. In contrast, our interpreter updates in milliseconds (median ∼14 ms on the first pass and 5–35 ms on the second), yielding *orders-of-magnitude* lower edit-to-inspect latency. This difference is qualitative: it enables near-keystroke feedback, which changes how developers explore code. Because results are symbolic, a single pass summarizes many concrete executions; developers can see when guards always hold/fail for an interval, when a branch becomes unreachable, or when a value may cross a critical threshold—all without leaving the editor. In short, SolQDebug complements runtime debuggers by moving fast, informative checks *into* the authoring loop (RQ1).

RQ2 shows that, in division-normalized patterns common in Solidity, *how* intervals are shaped can matter more than *which* arithmetic operator is used. Overlapping inputs systematically produced smaller output ranges than disjoint inputs, delaying or avoiding early widening. When investigating arithmetic joins, start with partially overlapping intervals and widen only as needed; keep operands aligned where normalization is present.

RQ3 demonstrates that loop precision is governed by the adaptive widening threshold τ, which depends on whether the loop condition expression can be evaluated in the pre-loop symbolic environment. Constant-bounded loops (`for (i = 1; i <= 4; ...)`) converge precisely without annotations because EstimateIterations computes exact thresholds. State-dependent loops (`for (i = 0; i < arr.length; ...)`) benefit directly from annotations: specifying `arr.length = 10` allows the analyzer to set $\tau = 10$, deferring widening and enabling natural convergence. However, data-dependent loops—where the loop body contains branches or updates decoupled from the index—may still widen despite accurate iteration counts, as the interval domain cannot track element-specific correlations.

Practical implications: (i) always annotate array lengths, mapping sizes, and iteration bounds for state-dependent loops to raise τ and delay widening; (ii) for data-dependent loops, use narrower annotations that materialize only the specific keys or elements under inspection, reducing the variability introduced by path merging; (iii) when widening becomes unavoidable (e.g., search loops over large collections), accept the over-approximation or switch to concrete inputs for targeted verification.

Overall, these findings suggest a debugging workflow that starts symbolic and broad, then *shapes* annotations to tighten precision where it matters (overlap, narrow, guard-guided), and finally uses concrete spot checks only for stubborn hot spots (e.g., deeply data-dependent loops).

5.3 Limitation

Our current scope and measurements introduce several limitations. First, we focus on single-contract, single-transaction functions. Inter-contract calls, multi-transaction workflows, proxies, and inheritance hierarchies are out of scope in the present implementation. As a result, we have not yet conducted a developer study in larger project settings; the usability and interpretability of edit-time feedback across multi-contract workflows remain unvalidated.

Second, our latency numbers combine interpreter execution time (timed in Python) with an estimate for annotation effort per variable (manual input). This procedure ignores UI-event latency and cursor dynamics, and it assumes a consistent operator for annotation entry. Likewise, our precision metric (F_{90}: 90th percentile of exit-/input-width inflation) captures a salient aspect of interval growth but does not reflect all developer notions of "useful precision." These choices provide a consistent basis for tool-level comparison but may under- or over-estimate end-to-end IDE latency or perceived precision.

We plan to (i) extend the analysis to inter-contract calls and multi-transaction scenarios, (ii) instrument editor events to directly measure human-in-the-loop latency and refine the annotation cost model, and (iii) run a controlled developer study once multi-contract support stabilizes. On the analysis side, loop summarization and selective use of lightweight relational domains (e. g., applied on demand to hot spots) are promising avenues to improve precision while preserving interactivity.

6 Related Works

6.1 Solidity IDEs and Debuggers

Modern Solidity development environments either embed a debugger or integrate external debugging plug-ins. Remix IDE (20) is the most widely used web IDE; it supports syntax highlighting, one-click compilation, and a bytecode-level debugger that lets users step through EVM instructions and inspect stack, memory, and storage. Hardhat (9) is a Node. js–based framework that couples the Solidity compiler with an Ethereum runtime; its Hardhat Debug plug-in attaches a Remix-style debugger to locally broadcast transactions inside Visual Studio Code. Foundry Forge (5) is a command-line toolchain oriented toward fast, reproducible unit testing; the command `forge test` spins up an ephemeral fork, deploys contracts, executes annotated test functions, and enables replay through Forge Debug. Solidity Debugger Pro (27) is a Visual Studio Code extension that performs runtime debugging over concrete transactions and integrates with Hardhat; in practice, many workflows create a small auxiliary contract that calls the target functions so that state changes can be observed step by step.

In short, these debuggers operate on compiled artifacts or post-deployment traces and rely on transaction replay and EVM-level stepping. They do not accept partial, in-flight source fragments nor provide symbolic (interval) input modeling or millisecond edit-time feedback. By contrast, SolQDebug targets pre-deployment authoring, accepts partial fragments and symbolic annotations, and reports line-level effects via abstract interpretation during editing.

6.2 Solidity Vulnerability Detection and Verification

A rich body of work analyzes smart contracts for security issues using four main families of techniques. Static analysis tools reason over source or bytecode without running the contract. Representative systems include rule- or pattern–based analyzers such as Securify and Slither (33; 34), symbolic-execution–assisted detectors like Mythril (36), knowledge-graph–based reasoning such as Solidet (10), and bytecode CFG refinement as in Ethersolve (19). Dynamic testing and fuzzing exercise deployed or locally simulated contracts to uncover faults and security issues: ContractFuzzer mutates ABI-level inputs (12), Echidna brings property-based fuzzing into developer workflows (6), sFuzz adapts scheduling for higher coverage (18), TransRacer finds transaction-ordering races (15), and Ityfuzz leverages snapshotting to decouple executions from chain nondeterminism (23). Formal verification aims to prove safety properties or refute counterexamples at compile time; examples include ZEUS, VeriSmart, and SmartPulse (13; 24; 32). Finally, AI-based approaches train models to predict vulnerabilities or triage candidates, e. g., via data-flow–aware pretraining, IoT-oriented classifiers, or prompt-tuning for detector adaptation (35; 37; 39).

These approaches have substantially advanced vulnerability detection and property checking for fully written contracts. However, they are not designed to provide interactive, edit-time feedback to developers while code is still under construction. They typically analyze post-compilation artifacts or deployed bytecode and expect complete program units. SolQDebug complements this line of work by focusing on pre-deployment authoring: it accepts partial fragments and symbolic (interval) inputs and produces line-by-line feedback inside the editor.

6.3 Solidity-Specific Abstract Interpretation Frameworks

Abstract interpretation is a well-established framework for static analysis and has been adapted to many programming languages. Two recent studies apply it to Solidity (7; 8). The first uses the Pos domain to construct a theoretical model for taint (information-flow) analysis Halder et al. (7), while the second employs the Difference-Bound Matrix (DBM) domain to generate state invariants and detect re-entrancy vulnerabilities, including the DAO attack (8; 16). However, both approaches operate on fully written contracts and provide no support for line-by-line interpretation or developer interaction within an IDE.

SolQDebug adapts abstract interpretation for an interactive setting. It incrementally updates both the control-flow graph and the abstract state in response to each edit. Developer-supplied annotations serve as a first-class input mechanism, reflecting how debugging often involves varying symbolic inputs. These annotations are internally represented as linear-inequality constraints, and form an integral part of interactive debugging by enabling symbolic reasoning over developer-specified inputs. This design improves interpretability and control within the interval domain by leveraging symbolic constraints, while maintaining keystroke-level responsiveness. As a result, SolQDebug updates variable ranges directly in the Solidity editor, allowing developers to observe how values evolve in response to each edit.

6.4 Interactive Abstract Interpretation for Traditional Languages

In recent years, traditional languages have seen a surge of interest in making abstract interpretation interactive, integrating it directly into IDEs to provide live analysis feedback during editing (1; 4; 21; 30; 31). Stein et al. (30) proposed demanded abstract interpretation, which incrementally rebuilds only the analysis nodes touched by an edit. A follow-up Stein et al. (31) generalized this to procedure summaries, enabling inter-procedural reuse. Erhard et al. (4) extended Goblint with incremental support for multithreaded C, selectively recomputing only genuinely affected facts and maintaining IDE-level responsiveness. Riouak et al. (21) introduced IntraJ, an LSP-integrated analyzer for Java 11 that computes only the AST and data-flow facts needed for the current view, keeping feedback under 100 ms. Chimdyalwar (1) achieved fast yet precise interval analysis on call graphs via one top-down and multiple bottom-up passes, and later introduced an incremental variant that revisits only the impacted functions.

Unlike these frameworks for C or Java, SolQDebug is designed specifically for Solidity. It supports in-flight code fragments and range annotations as first-class input. It incrementally updates only the current basic block in the CFG while reusing previously computed abstract states. Finally, it combines these with an interval domain guided by developer-supplied annotations, which act as input to represent the exploratory nature of debugging. This architecture enables keystroke-level feedback without requiring recompilation, redeployment, or transaction execution. It bridges the gap between Solidity development and the interactive tooling common in traditional programming environments.

7 Conclusion

We introduced SolQDebug, a source-level interactive debugger for Solidity that provides millisecond feedback without requiring compilation, deployment, or transaction replay. By combining interactive parsing, dynamic control-flow graph updates, and interval domain based abstract interpretation seeded by annotations, SolQDebug enables responsive, line-by-line inspection directly within the Solidity editor. Our evaluation shows that it reduces debugging latency compared to Remix, while enabling actionable feedback in response to symbolic inputs. These results demonstrate that SolQDebug's design effectively bridges the interactivity gap in Solidity debugging and brings the development experience closer to that of modern debugging workflows.

Future work includes extending SolQDebug to inter-contract and multi-transaction contexts, incorporating loop summarization for higher precision, and conducting user studies to assess its practical adoption and usability. We also plan to apply analysis based on the EVM Object Format (EOF) to support inter-contract debugging when source code is unavailable, as Ethereum moves toward structured bytecode formats in upcoming hard forks.

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A Interactive Parser Grammar Specification

This appendix provides the complete grammar specification for SolQDebug's interactive parser.

A.1 Entry Rules for Solidity Program Fragments

A.1.1 Rule 1: `interactiveSourceUnit`

Purpose. Accepts top-level declarations: functions, contracts, interfaces, libraries, state variables, pragmas, and imports.
Grammar:

```
interactiveSourceUnit
  : (interactiveStateVariableElement | interactiveFunctionElement
    | interfaceDefinition | libraryDefinition | contractDefinition
    | pragmaDirective | importDirective)* EOF ;
```

A.1.2 Rule 2: `interactiveEnumUnit`

Purpose. Accepts enum member items added after the enum shell.
Grammar:

```
interactiveEnumUnit : (interactiveEnumItems)* EOF;
interactiveEnumItems : identifier (',' identifier)*;
```

A.1.3 Rule 3: `interactiveStructUnit`

Purpose. Accepts struct member declarations added after the struct shell.
Grammar:

```
interactiveStructUnit : (structMember)* EOF;
structMember : typeName identifier ';' ;
```

A.1.4 Rule 4: `interactiveBlockUnit`

Purpose. Accepts statements and control-flow skeletons inside function bodies.
Grammar:

```
interactiveBlockUnit
  : (interactiveBlockItem)* EOF;

interactiveBlockItem
  : interactiveStatement | uncheckedBlock;

interactiveStatement
  : interactiveSimpleStatement
  | interactiveIfStatement
```

```
  | interactiveForStatement
  | interactiveWhileStatement
  | interactiveDoWhileDoStatement
  | interactiveTryStatement
  | returnStatement
  | emitStatement
  | revertStatement
  | requireStatement
  | assertStatement
  | continueStatement
  | breakStatement
  | assemblyStatement;

interactiveIfStatement
  : 'if' '(' expression ')' '{' '}' ;

interactiveForStatement
  : 'for' '(' (simpleStatement | ';') expression? ';' expression? ')' '{' '}' ;

interactiveWhileStatement
  : 'while' '(' expression ')' '{' '}' ;

interactiveDoWhileDoStatement
  : 'do' '{' '}' ;

interactiveTryStatement
  : 'try' expression ('returns' '(' parameterList ')')? '{' '}' ;
```

The `interactiveStatement` production includes skeleton rules for control structures with empty bodies (e.g., `interactiveIfStatement`, `interactiveForStatement`), enabling incremental construction of control flow. As developers type statements inside these empty bodies, `interactiveBlockUnit` is recursively invoked to parse each new line.

A.1.5 Rule 5: `interactiveDoWhileUnit`

Purpose. Accepts the `while` tail of a `do{...}` loop.
Grammar:

```
interactiveDoWhileUnit : (interactiveDoWhileWhileStatement)* EOF;
interactiveDoWhileWhileStatement : 'while' '(' expression ')' ';' ;
```

A.1.6 Rule 6: `interactiveIfElseUnit`

Purpose. Accepts `else` or `else if` branches.
Grammar:

```
interactiveIfElseUnit : (interactiveElseStatement)* EOF;
interactiveElseStatement : 'else' (interactiveIfStatement | '{' '}') ;
```

A.1.7 Rule 7: `interactiveCatchClauseUnit`

Purpose. Accepts `catch` clauses following a `try`.
Grammar:

```
interactiveCatchClauseUnit : (interactiveCatchClause)* EOF;
interactiveCatchClause : 'catch' (identifier? '(' parameterList ')')? '{' '}' ;
```

A.2 Entry Rule for Debugging Annotations

A.2.1 `debugUnit`

Purpose. Parses batch-annotation lines that specify initial abstract values for variables.
Annotation types:

- `@GlobalVar`: Assigns values to global variables (e.g., `msg.sender`, `block.timestamp`)
- `@StateVar`: Assigns values to contract state variables
- `@LocalVar`: Assigns values to function parameters and local variables

Grammar:

```
debugUnit : (debugGlobalVar | debugStateVar | debugLocalVar)* EOF;
debugGlobalVar : '//' '@GlobalVar' identifier ('.' identifier)? '=' globalValue ';' ;
debugStateVar : '//' '@StateVar' lvalue '=' value ';' ;
debugLocalVar : '//' '@LocalVar' lvalue '=' value ';' ;
```

Supported L-value patterns: Simple variables, array/mapping access (`arr[i]`, `map[key]`), struct fields (`s.field`), and nested combinations.
Value specification: Integer intervals `[l,u]`, symbolic addresses `symbolicAddress n`, boolean values, and symbolic placeholders.

B Abstract Domain and Formal Semantics

This appendix presents the abstract domain definitions and formal semantics used by SolQDebug's abstract interpreter. The framework is based on interval analysis for numeric types, set domains for addresses, and lazy materialization for composite data structures.

B.1 Abstract Domain

Atomic abstract values:

- **Unsigned integers:** $\widehat{\mathbb{U}}_N = \{[\ell, u] \mid 0 \le \ell \le u \le 2^N - 1\} \cup \{\bot, \top_N\}$

- **Signed integers:** $\widehat{\mathbb{Z}}_N = \{[\ell, u] \mid -2^{N-1} \le \ell \le u \le 2^{N-1}-1\} \cup \{\bot, \top^{\pm}_N\}$
- **Booleans:** $\widehat{\mathbb{B}} = \{\bot, \widehat{\mathsf{false}}, \widehat{\mathsf{true}}, \top\}$
- **Addresses:** $\widehat{\mathbb{A}} = \wp_{\le K}(\mathsf{AddrID}) \cup \{\top\}$ (set domain with cap $K = 8$)
- **Bytes:** $\widehat{\mathbb{BY}}_K = \{\bot, \top_K\}$ (symbolic/opaque)
- **Enums:** $\widehat{\mathsf{Enum}}(E) = \{[\ell, u] \mid 0 \le \ell \le u \le |E| - 1\} \cup \{\bot, \top_E\}$

Composite values:

- **Structs:** $\widehat{\mathsf{Struct}}(C) = \prod_{f \in \mathsf{fields}(C)} \widehat{\mathsf{Val}}_f$ (pointwise order)
- **Arrays:** $\widehat{\mathsf{Arr}}(\tau) = (\hat{\ell}, \hat{d}, M)$ where $\hat{\ell} \in \widehat{\mathbb{U}}_{256}$ is length, $\hat{d}$ is default element, $M : \mathbb{N}_{\text{fin}} \rightharpoonup \hat{\tau}$ stores observed indices
- **Mappings:** $\widehat{\mathsf{Map}}(\kappa \Rightarrow \tau) = (\hat{d}, M)$ with default $\hat{d}$ and finite map M for observed keys

Order, join, and meet: For intervals: $[\ell_1, u_1] \sqsubseteq [\ell_2, u_2] \iff \ell_2 \le \ell_1 \wedge u_1 \le u_2$, $[\ell_1, u_1] \sqcup [\ell_2, u_2] = [\min(\ell_1, \ell_2), \max(u_1, u_2)]$, $[\ell_1, u_1] \sqcap [\ell_2, u_2] = [\max(\ell_1, \ell_2), \min(u_1, u_2)]$ if non-empty, else $\bot$.

Widening ∇ and narrowing Δ follow standard interval analysis patterns. For address sets: $S_1 \sqcup S_2 = S_1 \cup S_2$ if $|S_1 \cup S_2| \le K$, else $\top$.

B.2 Concrete Semantics (Denotational)

Let stores be $\sigma : \mathsf{Var} \rightharpoonup \mathsf{CVal}$. L-value resolution $\mathrm{loc}_\sigma(lv) = \ell$ and write $\mathrm{write}(\sigma, \ell, v)$ update the store. Expressions are pure: $[\![e]\!]_\sigma \in \mathsf{Val}$.
Outcome domain:

$$\mathsf{Res} \ ::= \ \mathsf{Norm}(\sigma) \ \mid \ \mathsf{Ret}(v, \sigma) \ \mid \ \mathsf{Abort}$$

with sequencing

$$\begin{aligned} \mathsf{Norm}(\sigma) \ &\triangleright \ K := K(\sigma), \\ \mathsf{Ret}(v, \sigma) \ &\triangleright \ K := \mathsf{Ret}(v, \sigma), \\ \mathsf{Abort} \ &\triangleright \ K := \mathsf{Abort}. \end{aligned}$$

Array/mapping materialization: $\mathrm{loc}_\sigma(a[i])$ extends a up to i with defaults if needed; $\mathrm{loc}_\sigma(m[k])$ creates $m[k]$ lazily if absent.

B.3 Abstract Semantics (Denotational)

Let $\hat{\sigma} : \mathsf{Var} \rightharpoonup \widehat{\mathsf{CVal}}$ be the abstract store. Expressions evaluate to $[\![e]\!]^\sharp_{\hat{\sigma}} \in \widehat{\mathsf{Val}}$.
Abstract outcomes:

$$\widehat{\mathsf{Res}} \ ::= \ \widehat{\mathsf{Norm}}(\hat{\sigma}) \ \mid \ \widehat{\mathsf{Ret}}(\hat{v}, \hat{\sigma}) \ \mid \ \widehat{\mathsf{Abort}},$$

Table 6: Concrete denotational semantics (statements)

Statement	**Meaning**
skip	$[\![\mathsf{skip}]\!](\sigma) = \mathsf{Norm}(\sigma)$
$s_1; s_2$	$[\![s_1; s_2]\!](\sigma) = \big([\![s_1]\!](\sigma)\big) \ \triangleright\ (\lambda\sigma'.\, [\![s_2]\!](\sigma'))$
$\tau\ x;$	$[\![\tau\ x;]\!](\sigma) = \mathsf{Norm}\big(\sigma[x \mapsto \mathrm{zero}_\tau]\big)$
$\tau\ x = e;$	$[\![\tau\ x = e;]\!](\sigma) = \mathsf{Norm}\big(\sigma[x \mapsto [\![e]\!]_\sigma]\big)$
$lv := e$	$[\![lv := e]\!](\sigma) = \mathsf{Norm}\big(\mathrm{write}(\sigma,\, \mathrm{loc}_\sigma(lv),\, [\![e]\!]_\sigma)\big)$
$\mathsf{delete}\ lv$	$[\![\mathsf{delete}\ lv]\!](\sigma) = \mathsf{Norm}\big(\mathrm{write}(\sigma,\, \mathrm{loc}_\sigma(lv),\, \mathrm{zero}_{\tau(lv)})\big)$
$\mathsf{if}\ p\ \mathsf{then}\ s_t\ \mathsf{else}\ s_f$	$[\![\cdot]\!](\sigma) = \begin{cases} [\![s_t]\!](\sigma) & \text{if } [\![p]\!]_\sigma = \mathsf{true}, \\ [\![s_f]\!](\sigma) & \text{if } [\![p]\!]_\sigma = \mathsf{false} \end{cases}$
$\mathsf{while}\ p\ \mathsf{do}\ s$	$F(H)(\sigma) = \begin{cases} \big([\![s]\!](\sigma)\big) \ \triangleright\ H & \text{if } [\![p]\!]_\sigma = \mathsf{true}, \\ \mathsf{Norm}(\sigma) & \text{if } [\![p]\!]_\sigma = \mathsf{false} \end{cases}; \ [\![\mathsf{while}\ p\ \mathsf{do}\ s]\!] = \mathrm{lfp}(F)$
$\mathsf{return}\ e$	$[\![\mathsf{return}\ e]\!](\sigma) = \mathsf{Ret}([\![e]\!]_\sigma,\, \sigma)$
$\mathsf{assert}(p)$, $\mathsf{require}(p)$	$[\![\cdot]\!](\sigma) = \begin{cases} \mathsf{Norm}(\sigma) & \text{if } [\![p]\!]_\sigma = \mathsf{true}, \\ \mathsf{Abort} & \text{if } [\![p]\!]_\sigma = \mathsf{false} \end{cases}$
$\mathsf{revert}(\cdots)$	$[\![\mathsf{revert}(\cdots)]\!](\sigma) = \mathsf{Abort}$
$\mathsf{call}(\overline{e})$	Internal: parameter binding; external: unspecified

with sequencing

$$\begin{aligned} \widehat{\mathsf{Norm}}(\hat\sigma) \ \triangleright^\sharp\ K &:= K(\hat\sigma), \\ \widehat{\mathsf{Ret}}(\hat v, \hat\sigma) \ \triangleright^\sharp\ K &:= \widehat{\mathsf{Ret}}(\hat v, \hat\sigma), \\ \widehat{\mathsf{Abort}} \ \triangleright^\sharp\ K &:= \widehat{\mathsf{Abort}}. \end{aligned}$$

Auxiliary functions:

- $\mathrm{refine}(\hat\sigma, p, b)$: narrows operands of p by interval meets
- $\widehat{\mathrm{write}}(\hat\sigma, lv, \hat v)$: strong update if singleton index/key, weak update otherwise
- $\mathrm{joinRes}(r_1, r_2)$: componentwise join of abstract outcomes

Expression semantics: Arithmetic $(+, -, *, /, \%)$: interval arithmetic with wrapping; comparisons $(<, \leq, =, \neq, \geq, >)$: abstract booleans; logical $(\wedge, \vee, \neg)$: three-valued logic.
Array/mapping access: Singleton index/key: strong update; range/non-singleton: join of materialized cells.

Table 7: Abstract denotational semantics (statements)

Statement	**Meaning**
skip	$[\![\mathsf{skip}]\!]^\sharp(\hat\sigma) = \widehat{\mathsf{Norm}}(\hat\sigma)$
$s_1; s_2$	$[\![s_1; s_2]\!]^\sharp(\hat\sigma) = \big([\![s_1]\!]^\sharp(\hat\sigma)\big) \ \triangleright^\sharp \ (\lambda\hat\sigma'.\, [\![s_2]\!]^\sharp(\hat\sigma'))$
$\tau\ x;$	$[\![\tau\ x;]\!]^\sharp(\hat\sigma) = \widehat{\mathsf{Norm}}\big(\hat\sigma[x \mapsto \widehat{\mathrm{init}}(\tau)]\big)$
$\tau\ x = e;$	$[\![\tau\ x = e;]\!]^\sharp(\hat\sigma) = \widehat{\mathsf{Norm}}\big(\hat\sigma[x \mapsto \alpha_\tau([\![e]\!]^\sharp_{\hat\sigma})]\big)$
$lv := e$	$[\![lv := e]\!]^\sharp(\hat\sigma) = \widehat{\mathsf{Norm}}\big(\widehat{\mathrm{write}}(\hat\sigma,\ lv,\ [\![e]\!]^\sharp_{\hat\sigma})\big)$
delete lv	$[\![\mathsf{delete}\ lv]\!]^\sharp(\hat\sigma) = \widehat{\mathsf{Norm}}\big(\widehat{\mathrm{write}}(\hat\sigma,\ lv,\ \widehat{\mathrm{zero}}_{\tau(lv)})\big)$
if p then s_t else s_f	$\hat\sigma_t = \mathrm{refine}(\hat\sigma, p, \mathsf{true})$, $\hat\sigma_f = \mathrm{refine}(\hat\sigma, p, \mathsf{false})$; $[\![\cdot]\!]^\sharp(\hat\sigma) = \mathrm{joinRes}\big([\![s_t]\!]^\sharp(\hat\sigma_t),\ [\![s_f]\!]^\sharp(\hat\sigma_f)\big)$
while p do s	$G^\sharp(H)(\hat\sigma) = \mathrm{joinRes}\big([\![s]\!]^\sharp(\mathrm{refine}(\hat\sigma, p, \mathsf{true})) \triangleright^\sharp H,\ \widehat{\mathsf{Norm}}(\mathrm{refine}(\hat\sigma, p, \mathsf{false}))\big)$; $[\![\mathsf{while}\ p\ \mathsf{do}\ s]\!]^\sharp = \mathrm{lfp}^\nabla(G^\sharp) \bigtriangleup \mathrm{narrow}^k$
return e	$[\![\mathsf{return}\ e]\!]^\sharp(\hat\sigma) = \widehat{\mathsf{Ret}}([\![e]\!]^\sharp_{\hat\sigma},\ \hat\sigma)$
assert(p), require(p)	$\widehat{\mathsf{Norm}}(\mathrm{refine}(\hat\sigma, p, \mathsf{true}))$ if p must-hold; $\widehat{\mathsf{Abort}}$ if p must-fail; joinRes otherwise
revert$(\cdots)$	$[\![\mathsf{revert}(\cdots)]\!]^\sharp(\hat\sigma) = \widehat{\mathsf{Abort}}$
call$(\overline{e})$	Internal: parameter binding; external: havoc footprint or $\widehat{\mathsf{Abort}}$