Ethainter: A Smart Contract Security Analyzer for Composite Vulnerabilities

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Abstract

Smart contracts on permissionless blockchains are exposed to inherent risks due to interactions with untrusted entities. Static analyzers are essential for identifying security risks in smart contracts and avoiding losses of millions of dollars.

We introduce Ethainter, a security analyzer checking information flow with data sanitization in smart contracts. Ethainter identifies composite attacks that involve escalation of tainted information, through multiple transactions, leading to severe violations. The analysis scales to the entire blockchain, consisting of hundreds of thousands of unique smart contracts, deployed over millions of accounts. Ethainter is more precise than previous approaches, as we confirm by automatic exploit generation (e.g., destroying over 800 contracts on the Ropsten network) and by manual inspection, showing very high precision of 82.5% valid warnings for end-to-end vulnerabilities. Ethainter's precision and completeness compare very favorably to other tools such as Securify, Securify2, and teEther, in possibly the most extensive experiment of contrasting smart contract analyses in the literature.

CCS Concepts: • **Software and its engineering** → **General programming languages**; • **Social and professional topics** → *History of programming languages.*

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1 Introduction

Permissionless blockchain platforms such as Bitcoin [27] and Ethereum [6, 40] promise to revolutionize all sectors of multiparty interaction, by enabling decentralized, resilient consensus. The Ethereum platform, in particular, allows the execution of arbitrary programs, which are called *smart contracts*. Smart contracts are registered immutably on the blockchain and operate autonomously. Software correctness in smart contracts is critical, as (1) the contracts are high value targets (since they manage monetary assets), (2) are immutable and cannot be patched, and (3) are fully available for inspection (and invocation) by potential attackers. The need for contract correctness has gained prominence via several recent high profile incidents resulting in losses of cryptocurrency amounts valued in the hundreds of millions [8, 39].

Smart contracts are Turing-complete programs, typically expressed in a domain-specific language called Solidity [38]. Solidity contracts are compiled to low-level bytecode and executed by the Ethereum Virtual Machine (EVM) on the blockchain. Smart contracts store data either on the blockchain or in execution-ephemeral memory. Solidity programs implement unconventional data structures using cryptographic hashing, posing a challenge for static bytecode analyzers. Furthermore, EVM bytecode does not explicitly expose control flow, necessitating sophisticated decompilation methodologies [5, 12]. Hence, checking for even basic security vulnerabilities is non-trivial, as security analyzers for smart contracts require complex techniques to overcome these challenges [13, 35].

With the rising awareness of Ethereum security risks and the development of recommended practices, realistic attacks have become increasingly complex. They often chain successive exploits that each expose more vulnerabilities. A new class of security analyzers is required to identify such *composite* attacks. The most notorious (albeit relatively simple) example of a composite attack is the Parity wallet hack, where the equivalent of $280M [8] was stolen or frozen via two separate vulnerabilities. The attack involved reinitializing part of the contract that sets owner variables, via a vulnerable library function, before subsequently attacking the contract.

To safeguard against sophisticated attacks, it is essential to model the information flow [31] inside smart contracts accurately. Information flow classifies information into trusted and untrusted and considers how it propagates in the code. For example, if untrusted ("tainted") information from external sources is allowed to spread to critical program points, it can alter key aspects of program behavior.

Smart contract programmers employ guarding patterns to prevent an untrusted entity from executing sensitive operations, such as destroying the contract. For example, the contract code could check whether the user of the contract (a.k.a., its *caller* or *sender*) has specific privileges. The simplest check is to permit only a particular contract owner account to perform critical actions. For security analyzers, it is essential to model this guarding mechanism, for any high-fidelity information flow analysis: if guards are not taken into consideration, many contracts will be incorrectly inferred to be vulnerable, when the only user that can "exploit" these vulnerabilities would be the owner of the contract themselves. Conversely, the guarding code can itself be attacked, by invoking code that manipulates the state of the contract in unexpected ways.

In this work, we present Ethainter: the first security analyzer for detecting composite information flow violations in Ethereum smart contracts. Ethainter enhances the understanding of tainted information flow with the tainting of guard conditions, other potential ineffectiveness of guards, as well as different kinds of taint that are not prevented by guarding. Ethainter models not just the existence of guards but also whether they are effective in sanitizing information. The specification of the analysis is in a formalism of independent value. It ignores orthogonal, well-understood technical complexities, capturing, instead, the essence of new information flow concepts (e.g., tainted guards, taint through storage) in minimal form. For example, we consider a tainted memory store to induce further information flow more eagerly than an untainted (yet still statically undetermined) memory store. The precision, recall, and scalability of Ethainter are highly fine-tuned using mutually-recursive Datalog rules for tainting and overall information flow. The contribution of our work is as follows:

- We formulate an information flow analysis for smart contracts that takes into account the sanitization (i.e., guarding) coding practices in smart contracts, as well as attacks that circumvent them.
- The precision and recall of Ethainter are highly-tuned, in a sophisticated recursive analysis. As a result, Ethainter exhibits very high precision (82.5%, based on manual inspection of a random sample of flagged contracts).
- The Ethainter implementation is highly scalable, applying to the entire set of unique smart contracts on the Ethereum blockchain (around 38MLoC) in 6 hours.
- Ethainter's companion tool, Ethainter-Kill, can automatically exploit (on live Ethereum networks) one of the security violations flagged by Ethainter. Ethainter-Kill has destroyed over 800 smart contracts on a fork of the Ropsten Network (16.67% of the flagged contracts) confirming Ethainter's practical relevance and a high lower bound for Ethainter's end-to-end precision.
- We perform a comparison of Ethainter with different tools for smart contract security analysis: Securify [35], Securify2 [**?**], and teEther [22]. The tools cover different points in the design space (e.g., symbolic execution for teEther [22]) and their contrast is highly instructive. Ethainter compares very favorably to all tools in terms of combining precision (i.e., low false-positive rate) and completeness (i.e., finding more vulnerabilities).

2 Illustration

Composite vulnerabilities escalate a weakness through multiple transactions, resulting in increasingly more tainted elements of a contract. Consider an abstracted example:

```
contract Victim {
 mapping(address => bool) admins;
 mapping(address => bool) users;
 address owner;

 modifier onlyAdmins() {
   require(admins[msg.sender]);
   _;
 }
 modifier onlyUsers() {
   require(users[msg.sender]);
   _;
 }

 function registerSelf() public
  { this.users[msg.sender] = true; }

 function referUser(address user) public onlyUsers
  { this.users[user] = true; }

 function referAdmin(address adm) public onlyUsers
  { this.admins[adm] = true; }

 function changeOwner(address o) public onlyAdmins
  { this.owner = o; }

 function kill() public onlyAdmins
  { selfdestruct(self.owner); }
}
```

At first glance, the `Victim` contract is seemingly unsusceptible to the "accessible `selfdestruct`" vulnerability, as function `kill()` can only be called by administrators and, in any case, when called it only sends the contract's balance to the owner. Furthermore, all functions are guarded. Some are only accessible to registered users, some to admins and some to owners. However, the contract exhibits an error in the modifier of method `referAdmin`. This functionality, which adds administrators, should be protected by modifier `onlyAdmins` rather than `onlyUsers`—a mistake perhaps caused by the developer copying and pasting the `referUser` definition. As a consequence, an attacker may exploit the contract, in four successive steps, with each step invoking a separate internal transaction. This is encoded in the following attack:

```
contract Attacker {
 Victim victim = ...;

 function attack() public {
  victim.registerSelf();    // make myself a user
  victim.referAdmin(this); // make myself an admin
  victim.changeOwner(this);// make myself an owner
  victim.kill();           // destroy contract
 }
}
```

The attack starts by registering the attacker as a user, after which the attacker is (erroneously) allowed to add themselves to the list of admins, enabling them to call `changeOwner` to register themself as the owner. The attacker can then call `kill` to invoke a `selfdestruct` operation that destroys the smart contract and sends its funds to `self.owner` (the attacker).

Notably, there are two primitive vulnerabilities in this contract: "accessible `selfdestruct`" after the second step of the attack, and "tainted `selfdestruct`" after the fourth step. Our analysis can detect such vulnerabilities: the tainting of a guard condition successively enables more tainting, which invalidates guards that might locally appear sound. These vulnerabilities are described in further detail in the following Section.

3 Background: Kinds of Information Flow Vulnerabilities

We next present examples of (the building blocks of) information flow vulnerabilities in smart contracts, as well as the usual programming patterns that prevent them. We refer to these vulnerabilities by name in the rest of the paper. The presentation is intended to be simplified, showing the simplest form of every vulnerability, rather than combinations or occurrences in the wild.

3.1 Tainted Owner Variable

Smart contract programming languages, such as Solidity, typically offer `require`/`assert` features that guard a smart contract's execution. These guards are often a mechanism employed by the smart contract developer to protect against the execution of sensitive operations by untrusted parties.[1]

[1]Strictly speaking, only a `require` guard is appropriate for eliminating undesired input, but an `assert` is equally valuable for preventing an unexpected violation of contract invariants from propagating further.

Precise modeling of these guards is essential for reducing the number of false positives by any analysis. Guards can, however, be attacked by third parties, for instance, by misplaced constructor functions in libraries, as has happened in the notorious Parity wallet hack.

Numerous further attacks may happen when guards are successfully attacked. These attacks may result in economic consequences quickly. For instance, an attacker may want to artificially dilute or inflate the value of ERC20 tokens, functionality that would undoubtedly be guarded. We consider *Tainted Owner Variable* a vulnerability in its own right, however, this vulnerability may introduce other information flow vulnerabilities, such as making contract self-destruction accessible.

The following example shows a contract with a global variable `owner`, used in function `kill` to check whether the address of the caller of the contract (denoted `msg.sender`) is the same as the address of the owner of the contract. However, in this contract, a public setter function called `initOwner` makes it possible for anyone to update the `owner` to an arbitrary value, making the contract vulnerable.

```
address owner = ...;

function initOwner(address _owner) public {
    owner = _owner;
}

function kill() public {
    if (msg.sender == owner)
    { /* sensitive operations */ ... }
}
```

3.2 Tainted `delegatecall`

The EVM's `delegatecall` instruction allows any code that is called to make any state changes to the caller's contract, including sending funds to any address or destroying the contract. The *tainted* `delegatecall` vulnerability allows an attacker to cause the contract to call another, resulting in a high-risk security vulnerability. The following Solidity code shows a naïve function called `migrate` that allows any user to supply the address used by the `delegatecall`. Such functions could well exist as private members of a contract, for reasons of code reuse, but a vulnerability arises, e.g., when the function is publicly accessible or called from a publicly accessible function without guarding.

```
function migrate(address delegate) public {
    delegate.delegatecall.gas(msg.gas - 1500)();
}
```

3.3 Accessible `selfdestruct`

When the EVM's `selfdestruct` instruction is invoked, the contract is deactivated, and any remaining balance is sent to the address supplied. The following code demonstrates the pattern. Naturally, `selfdestruct` is a highly sensitive operation that results in the permanent termination of a contract, so it should be guarded.

```
function kill() public {
    selfdestruct(beneficiary);
}
```

This vulnerability is more commonly encountered in combination with a tainted guard.

3.4 Tainted `selfdestruct`

This vulnerability is a variant of the previous one, with a potential direct profit for an attacker. With a *tainted* `selfdestruct` vulnerability, the receiving address of the funds can be controlled by any user of the contract. Notice that, even though `selfdestruct` is not accessible by third-party users, any user can taint the address (held by an `administrator`), so that, when `selfdestruct` is finally called, any remaining balance will be transferred to the attacker.

```
address owner = ...;
address administrator = ...;

function initAdmin(address admin) public {
    administrator = admin;
}

function kill() public {
    if (msg.sender == owner) {
        selfdestruct(administrator);
    }
}
```

3.5 Unchecked Tainted `staticcall`

A recently introduced EVM opcode is `staticcall`. This can be used to call a smart contract, while disallowing any modifications to the state during the call. The `staticcall` opcode enables more secure smart contract development by allowing purely functional calls, thus disallowing state-modifying reentrancy.

A problematic `staticcall` is one where the return values do not overwrite the current memory buffer used for passing and returning data to `CALL` instructions. A recent example of this vulnerability was found in the 0x [1] decentralized exchange protocol. This vulnerability enabled a single wallet to sign off transactions that should have been signed off by multiple parties. An example of such suspect code (in Solidity assembly) is shown below. The output of the `staticcall` invocation is meant to overwrite its input. However, `staticcall` does not perform this unless the client that is called returns at least 32 bytes of data. Otherwise, the input is read as output. As a consequence, a tainted `staticcall` potentially allows the attacker to pass untrusted input as output from a trusted external call, fooling the caller.

```
let cdStart := add(calldata, 32)
let success := staticcall(
  walletAddress,    // address of Wallet contract
  cdStart,          // pointer to start of input
  mload(calldata),  // length of input
  cdStart,          // write output over input
  32                // output size is 32 bytes
)

switch success
...
case 1 {
    // Signature is valid if call did not revert
       and returned true
    isValid := mload(cdStart)
}
```

To defend against such a vulnerability, the latest Solidity compilers insert instructions that check first whether the called address has valid code. Besides, when the callee returns less than the minimum expected amount of data, the `RETURNDATASIZE` opcode is used to pad the output accordingly. As this issue was fixed less than a year ago, many unsafe libraries still exist which do not correctly handle these cases.

4 Information Flow Analysis Framework

In this section, we present a distilled, formalized version of our information-flow analysis on an abstract input language. The key tenet is to abstract away from the complexity of language elements keeping the focus on the detection of composite vulnerabilities. For this purpose, we design a small abstract input language that captures information flow semantics of smart contracts: it has taint sources and sinks, transfers through various operations, loads and stores to persistent storage, and input sanitization through guards. We provide information flow rules which we will mark as either an over- or an under-approximation. The emphasis of the formalism is to capture sufficient information-flow for the detection of composite vulnerabilities. We consider:

- programmatic guarding/sanitizing so that tainted input cannot be propagated,
- only caller input can be sanitized via guards, whereas, if taint propagates to the persistent storage of the contract, it can elude guards,
- the problem of tainting either arbitrary storage locations or the condition of a guard,
- the complex form of effective guards, possibly using the contract caller's address as a key into persistent data structures, to look up permissions, ownership, balances, etc.

4.1 Input and Output Schema

The syntax for the instructions of the abstract input language is shown in Figure 1. We use lowercase letters $(f, t, x, y, \ldots)$ to designate program variables. `sender` is a reserved variable

Instruction	:=	x := OP(y, z)	*operation, including arithmetic, boolean ops, equality, phi*
	|	x := INPUT()	*load input data: a taint source instruction*
	|	x := HASH(y)	*hash function (e.g., SHA3)*
	|	x := GUARD(p, y)	*value guarded by sender predicate: contract caller checked in predicate p to sanitize y*
	|	SSTORE(f, t)	*write to persistent storage: from local variable f to storage address t*
	|	SLOAD(f, t)	*load from persistent storage: from storage address f to local variable t*
	|	SINK(x)	*sensitive instruction: a taint sink*

Figure 1. Syntax of the source language instructions.

Relation	Notation	Description
InputTaintedVar	$\downharpoonleft^I x$	Variable x is tainted from input.
StorageTaintedVar	$\downharpoonleft^T x$	Variable x is tainted from storage.
TaintedStorage	$\downharpoonleft^T S(v)$	Storage location with constant address v is tainted.
NonSanitizingGuard	$\ddagger p$	Guard predicate p fails to sanitize.
ConstValue	$C(x) = v$	Variable x is inferred to have constant value v .
StorageAliasVar	$x \sim S(v)$	Variable x is inferred to be an alias for storage slot v .
SenderDataStructElem	DS(x)	x holds (aliases) a data structure element, whose key is the message sender's address.
SenderDataStructAddr	DSA(x)	x is the address of a data structure element, whose key is the message sender's address.

Figure 2. Relations computed by the information flow analysis. The first two are output relations, computed simultaneously (in mutual recursion) with the next two, while the last four are auxiliary relations. The auxiliary relations are computed before the output relations (i.e., do not depend on taint propagation, therefore their contents are fixed in a previous stratum in the fixpoint computation).

name, designating the caller of a contract. The input program is in three-address (i.e., all expressions are expanded, up to variables) static single-assignment (SSA) form (i.e., a variable name implicitly encodes a single program location—the variable's definition). SSA phi-instructions, for merging different versions of a variable, are mere OPs in our language. Equality is also an OP for most analysis purposes, however we sometimes need to refer to equality comparisons explicitly, in which case we write them in infix form, i.e., "x := $(y = z)$", is just an instance of an "x := OP(y, z)" with the operator being equality.

The GUARD instruction deserves some attention: "x := GUARD(p, y)" means that x receives a sanitized value from y if a predicate with truth value p is satisfied. This captures in terms of values (instead of guarded code statements) the common pattern of reading possibly-tainted inputs only when the `msg.sender` value (i.e., the contract's caller) satisfies some criterion: either it is equal to a known storage value, or it is looked up in a data structure of allowed callers. A single syntactic block guarded by, e.g., "`if (msg.sender == owner)`" is equivalent to multiple GUARD statements, sanitizing every caller-input value that may flow into this block, with a predicate such as "p := (sender = z)" (where z is the result of an SLOAD from the persistent storage location holding the contract's owner).

Figure 2 illustrates the relations computed by our information flow analysis. Note that there are two different kinds of taint values for variables, denoted by $\downharpoonleft^I x$ (*InputTaintedVar*) and $\downharpoonleft^T x$ (*StorageTaintedVar*). Taint from unsanitized user input can be eliminated by the use of sender guards, which ensure that the caller of a contract is approved. However, taint that has propagated into storage cannot be removed by the use of sender guards. The relation $\ddagger p$ (*NonSanitizingGuard*) captures conditions under which a guard fails to successfully sanitize caller input: either the guard condition is itself tainted, or the guard does not compare sender (either directly or by indexing into storage data structures).

Relations $C(x) = v$ (*ConstValue*) and $x \sim S(v)$ (*StorageAliasVar*) encode standard valueflow and alias analyses. These are the only relations whose definitions we elide, since they are entirely conventional and orthogonal to the information flow analysis. In fact, these can well be considered input relations, computed using extra information that is not present in the abstracted input language (e.g., function boundaries). Note that $x \sim S(v)$ applies only to storage locations indexed by a statically-known constant address. We complement this relation with a less strict, but more specialized, concept, of all (unknown) addresses/data reachable through storage data structures, based on `sender`, in relations DSA(x) and DS(x).

4.2 Information Flow Core Analysis

Figure 3 lists the rules of the information flow analysis. We employ some conventions for syntactic convenience: Wildcard symbol $*$ indicates a "don't care" value, for a variable or a taint flavor (i.e., "I" or "T", for input vs. storage taint). The notation $\downarrow^{I/T}$ also denotes either kind of taint, but all occurrences in the same rule are required to have matching taint kinds. We discuss the information flow rules in the following:

- LoadInput, Operation-1, Operation-2: These rules perform taint introduction and propagation through binary operators. (Note that, per our $\downarrow^{I/T}$ convention, the taint flavor that propagates is the same as the incoming one.) The only nuance is that taint from `INPUT` statements is explicitly designated as being input taint.
- Guard-1, Guard-2: The first rule states that storage taint (but not input taint) propagates through `GUARD` operations. Conversely, input taint propagates through `GUARD` operations only if the guard predicate is non-sanitizing.
- StorageWrite-1, StorageWrite-2: The first of these rules turns any kind of taint from a tainted source into storage taint, when written into a statically-known storage location. The second rule taints *all* such statically-known storage locations when the destination of the store operation is also tainted, capturing the high risk of tainted writes to addresses that may be influenced by an attacker.
- Violation, StorageLoad: Loads from tainted constant storage locations introduce storage taint into a local variable. Either kind of taint on an operand of a `SINK` instruction results in a reported violation. (Note that variables f and t, for "from" and "to", change types between the `SSTORE` and `SLOAD` commands—e.g., for `SLOAD`, f is the address, whereas, for `SSTORE`, t is.)
- Uguard-T, Uguard-NDS: The *NonSanitizingGuard* relation is established under two conditions: Either the guard predicate directly compares the contract caller to a tainted storage address, or the guard predicate does not involve (neither in its left- nor in its right-hand-side) values possibly based on `sender`, via direct reference or data structure lookup. The full definition of the latter concept is discussed in Section 4.3.

The analysis definition of Figure 3 makes the four relations $\downarrow^{I} x$, $\downarrow^{T} x$, $\downarrow^{T} S(v)$, and $\ddagger p$ mutually recursive. All of them grow monotonically, with each inference for one relation only able to lead to a growing set of inferences for others. Therefore, the rules can be directly translated to an algorithm for the analysis: the rules iterate starting from empty and up to fixpoint for all relations. Conversely, relation DS(x) is negated in rule Uguard-DS, therefore, its growing leads to fewer inferences for other relations (starting from $\ddagger p$). The evaluation of DS(x) is independent of taint propagation, however, and can complete before the main analysis, as described next.

4.3 Sender-Keyed Data Structure Lookups

Figure 4 shows the definition of relations DS(x) and DSA(x), which capture the notion of predicates that scrutinize the caller of a contract (by direct comparisons or in a persistent data structure). Per rule DS-SenderKey, the `sender` variable is a base case of information that pertains to the identity of a contract's caller. The only other way to produce a y that satisfies DS(y) is via rule DSA-Load: by dereferencing an address x that satisfies DSA(x). Therefore, most of the relevant rules concern relation DSA, i.e., the definition of *addresses* that may hold data pertaining to a contract's caller.

The rules conservatively capture the unconventional Ethereum memory layout and data structure policy. The hash function (`SHA3` in the EVM) is considered collision-free and used for a variety of mapping purposes, including data structure nesting. For instance, a 2-dimensional array `arr[][]` is typically identified merely by a constant storage location (e.g., `42`) that stores the length of the outer array (and not an address/pointer to its contents, as might be expected). Addresses are then "invented" by hashing: the contents of the array are found starting at location `HASH`(`HASH`(42)) for subarray `arr[0]`, location `HASH`(`HASH`(42)+1) for subarray `arr[1]`, etc. (Accordingly, location `HASH`(42) stores the length of subarray `arr[0]` and location `HASH`(42)+1 stores the length of subarray `arr[1]`.) Rule DS-Lookup encodes the hashing of caller-related information (DS(y)), to be used as a storage address. Rule DSA-Lookup captures nested data structures, i.e., hashes of addresses, as in our previous example, also aided by arithmetic on addresses, as shown in rules DS-AddrOp-1 and DS-AddrOp-2.

4.4 Analysis Design Discussion

We designed our information flow analysis keeping the *completeness* and *precision* of Ethainter's implementation in mind. The tradeoff between completeness and precision profoundly impacts the error detection of a security analyzer. In our design, we made conscious decisions when to *over-approximate*, which may introduce a higher false-positive rate, and when to *under-approximate*, obtaining high-confidence inferences of violations for improving precision at the cost of completeness. We summarize our design decisions below:

$$(\textsc{LoadInput})\ \frac{x\ \texttt{:=}\ \texttt{INPUT}()}{\downharpoonleft^{I} x}$$

$$(\textsc{Operation-1})\ \frac{x\ \texttt{:=}\ \texttt{OP}(y, *) \qquad \downharpoonleft^{I/T} y}{\downharpoonleft^{I/T} x} \qquad (\textsc{Operation-2})\ \frac{x\ \texttt{:=}\ \texttt{OP}(*, y) \qquad \downharpoonleft^{I/T} y}{\downharpoonleft^{I/T} x}$$

$$(\textsc{Guard-1})\ \frac{x\ \texttt{:=}\ \texttt{GUARD}(*, y) \qquad \downharpoonleft^{T} y}{\downharpoonleft^{T} x} \qquad (\textsc{Guard-2})\ \frac{x\ \texttt{:=}\ \texttt{GUARD}(p, y) \qquad \downharpoonleft^{I} y \qquad \ddagger p}{\downharpoonleft^{I} x}$$

$$(\textsc{StorageWrite-1})\ \frac{\texttt{SSTORE}(f, t) \qquad \downharpoonleft^{*} f \qquad C(t) = v}{\downharpoonleft^{T} S(v)} \qquad (\textsc{StorageWrite-2})\ \frac{\texttt{SSTORE}(f, t) \qquad \downharpoonleft^{*} f \qquad \downharpoonleft^{*} t}{\forall i : \downharpoonleft^{T} S(i)}$$

$$(\textsc{StorageLoad})\ \frac{\texttt{SLOAD}(f, t) \qquad \downharpoonleft^{T} S(v) \qquad C(f) = v}{\downharpoonleft^{T} t} \qquad (\textsc{Violation})\ \frac{\texttt{SINK}(x) \qquad \downharpoonleft^{*} x}{\textsc{violation}}$$

$$(\textsc{Uguard-T})\ \frac{p\ \texttt{:=}\ (\texttt{sender}\ \texttt{=}\ z) \qquad z \sim S(v) \qquad \downharpoonleft^{T} S(v)}{\ddagger p} \qquad (\textsc{Uguard-NDS})\ \frac{p\ \texttt{:=}\ (y\ \texttt{=}\ z) \qquad \neg\mathrm{DS}(y) \qquad \neg\mathrm{DS}(z)}{\ddagger p}$$

Figure 3. Inference rules for information flow analysis.

$$(\text{DS-}\textsc{SenderKey})\ \frac{}{\mathrm{DS}(\texttt{sender})}$$

$$(\text{DS-}\textsc{Lookup})\ \frac{x\ \texttt{:=}\ \texttt{HASH}(y) \qquad \mathrm{DS}(y)}{\mathrm{DSA}(x)} \qquad (\text{DSA-}\textsc{Lookup})\ \frac{x\ \texttt{:=}\ \texttt{HASH}(y) \qquad \mathrm{DSA}(y)}{\mathrm{DSA}(x)}$$

$$(\text{DS-}\textsc{AddrOp-1})\ \frac{\mathrm{DSA}(y) \qquad x\ \texttt{:=}\ \texttt{OP}(y, *)}{\mathrm{DSA}(x)} \qquad (\text{DS-}\textsc{AddrOp-2})\ \frac{\mathrm{DSA}(y) \qquad x\ \texttt{:=}\ \texttt{OP}(*, y)}{\mathrm{DSA}(x)}$$

$$(\text{DSA-}\textsc{Load})\ \frac{\mathrm{DSA}(x) \qquad \texttt{SLOAD}(x, y)}{\mathrm{DS}(y)}$$

Figure 4. Inference rules for identifying data structures in storage.

- Relations DS() and DSA() have an over-approximate definition: the rules of Figure 4 capture any dereference, arithmetic; an expression that may involve the key of the contract's caller (i.e., the value of the `sender` variable). However, the relation DS() is *negated* in the main information flow analysis (Figure 3), therefore the analysis about caller lookups is an under-approximation: it favors precision, avoiding warnings whenever the analysis establishes that a guard expression *might* be scrutinizing the contract's caller. Instead, warnings are emitted only in high confidence scenarios.
- As discussed earlier, auxiliary relations $C(x) = v$ (*ConstValue*) and $x \sim S(v)$ (*StorageAliasVar*) encode standard static value-flow and alias analyses. As conventional in static reasoning, the definition of such analyses is an over-approximation concerning control flow: whenever two program paths meet, the union of inferences is propagated. However, the formulation of the relations themselves is an under approximation: they are defined only for constant values (numeric values or storage addresses). This means that aliasing with a statically unknown storage location is not captured. Aliasing with a constant storage location through memory operations that involve runtime variable addresses is also not captured. This design decision means that the analysis favors precision: it establishes taint violations and tainted guards with high confidence only.
- The one analysis rule that over-approximates, is StorageWrite-2. If a store operation has both its value and its address tainted, then all constant storage locations

that arise in the analysis are considered tainted. This design choice focuses on completeness of the analysis, i.e., it increases its ability to capture errors, but possibly yields false positives.

4.5 Connecting to Practice

The simplified model we just presented captures many key aspects of the approach, including the different kinds of taint (storage vs. input) and the presence of guards. It misses, however, an orthogonal element which is essential in practice: the definition of taint sinks and guards. In the formalism (Figure 1) we considered guards and sinks to be an input of the analysis: syntactic forms of instructions (x := GUARD(p, y) and SINK(x)).

In reality, which condition of the program is a guard and which is a taint sink (i.e., a sensitive statement to be protected) can be information that the analysis itself computes, out of much lower-level statements. For guards, their computation is rather mundane—it is recursive with the main analysis, but hardly surprising: in essence, if a check dominates a use of a tainted variable, it is considered a guard for that variable. For taint sinks, the story can be even simpler: "accessible `selfdestruct`", "tainted `selfdestruct`", "unchecked tainted `staticcall`", "tainted `delegatecall`" all have the sensitive variable (or statement) clearly identified syntactically.

For the "tainted owner variable" vulnerability (Section 3.1), however, the computation of sinks is highly interesting. The analysis cannot know which storage location corresponds to the "owner" of a contract. Instead, it needs to compute which locations are sensitive. This computation is essential for precision. The analysis certainly should not flag all tainted writes to arbitrary storage locations, or it would warn about nearly all contracts.

To address this problem, taint sinks are computed in a way similar to tainted guards (rule UGUARD-T): a variable is a sink if its value is read from storage *and* it is used as a guard for another tainted variable. Slightly abusing our notation (since SINK is no longer an input instruction kind), we have:

$$\frac{* \texttt{ := GUARD(sender} = z, x\texttt{)} \qquad \downarrow^{I/T} x \qquad z \sim S(*)}{\texttt{SINK}(z)}$$

In intuitive terms, the analysis is trying to find which tainted locations are worth reporting. Guards are akin to real-life locks on doors. A merely unlocked door to a room does not elicit a warning (i.e., an unguarded or badly-guarded variable is not by itself a sink) unless the room has self-evidently sensitive contents (as in the case of "tainted `selfdestruct`", etc.). But the analysis *does* warn when it finds an unlocked door to a room that contains *keys* found to match a *locked* door: a variable that determines a potentially-sanitizing guard is by itself a sink.

5 Datalog Implementation

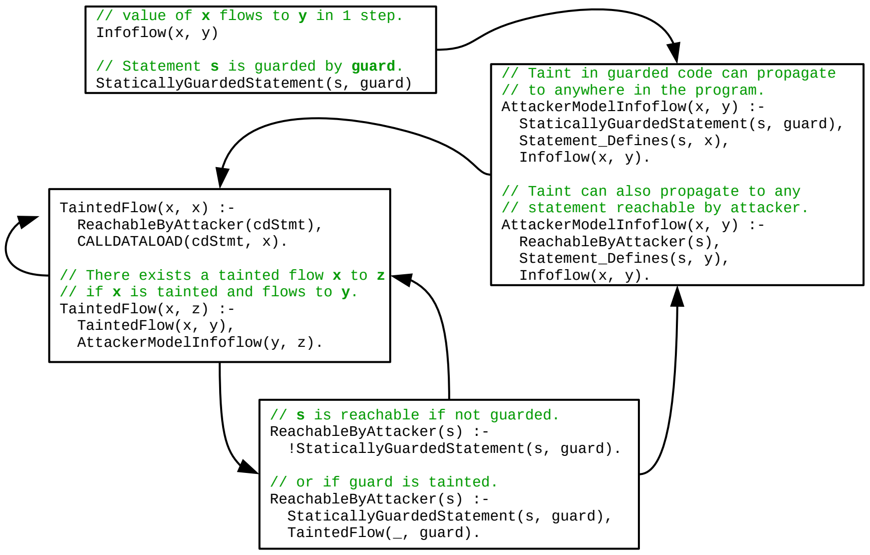
Ethainter implements the information flow model as a set of several hundred declarative rules in the Datalog language.

Ethainter's input is a set of logic relations containing a functional 3-address code representation of an EVM bytecode program. We obtain this representation by decompiling each contract using the Gigahorse toolchain [12]. The Ethainter implementation back-end is the high-performance Soufflé [20] Datalog engine, which translates Datalog input relations into highly optimized C++ code.

Our information flow analysis implementation is enriched with additional smart contract analyses to obtain further precision:

- The implementation uses intra-procedural constant propagation data flow analysis for propagating constant values (i.e., relation $C(x) = v$ of Section 4) and a call site sensitive analysis for computing storage locations that are aliases (i.e., relation $x \sim S(v)$). We have experimented with other options for more completeness or precision and believe that the above offer a good balance, hard to noticeably improve upon.
- In addition to tainting (i.e., data dependencies), our analysis also considers some control dependence patterns as information flow violations. The treatment is under-approximate by design: we only capture limited cases that have a high likelihood to be true vulnerabilities.
- In addition to the modeling of storage (i.e., persistent contract data on the blockchain), the analysis models "memory", i.e., data that pertain to a single transaction. Memory can still be inter-procedural, since the control flow of a transaction crosses different functions. Because memory is non-local (e.g., can be tainted in a function call in order to alter the execution several function calls later) taint flow through memory is often present in realistic vulnerabilities. The Ethainter modeling of memory mostly follows the principles used for storage in Section 4 but memory taint does get sanitized via guards, much like input taint.
- The implementation contains more complexity in dealing with patterns not fully captured in the input language of the model (e.g., accessible `selfdestruct`, which concerns reachable instructions and not tainted variables). Generally, this complexity is of the flavor expected when transiting from a highly simplified input language to realistic programs—the spirit of the analysis logic is well-captured by the simplified model.

The simplified core of the Datalog implementation is depicted in Figure 5, illustrating the mutual recursion between tainting, attacker-reachable code, and conditional information flow. In more detail: `ReachableByAttacker`



```
// value of x flows to y in 1 step.
Infoflow(x, y)

// Statement s is guarded by guard.
StaticallyGuardedStatement(s, guard)
```

```
// Taint in guarded code can propagate
// to anywhere in the program.
AttackerModelInfoflow(x, y) :-
  StaticallyGuardedStatement(s, guard),
  Statement_Defines(s, x),
  Infoflow(x, y).

// Taint can also propagate to any
// statement reachable by attacker.
AttackerModelInfoflow(x, y) :-
  ReachableByAttacker(s),
  Statement_Defines(s, y),
  Infoflow(x, y).
```

```
TaintedFlow(x, x) :-
  ReachableByAttacker(cdStmt),
  CALLDATALOAD(cdStmt, x).

// There exists a tainted flow x to z
// if x is tainted and flows to y.
TaintedFlow(x, z) :-
  TaintedFlow(x, y),
  AttackerModelInfoflow(y, z).
```

```
// s is reachable if not guarded.
ReachableByAttacker(s) :-
  !StaticallyGuardedStatement(s, guard).

// or if guard is tainted.
ReachableByAttacker(s) :-
  StaticallyGuardedStatement(s, guard),
  TaintedFlow(_, guard).
```

Figure 5. Skeleton of the core of the implementation in Datalog. Arrows depict complex recursion between the rules. `Infoflow` accounts for all flows, including inter-procedural flow and flows through data structures.

models which parts of the code are reachable by an attacker. The rules also model (via `AttackerModelInfoflow` and `TaintedFlow`) how information can flow in a model where the attacker can only execute certain parts of the program while a privileged user is not expected to introduce new tainted information to the state. `AttackerModelInfoflow` is a subset of the general taint analysis `Infoflow`, a single-step information flow relation which does not distinguish between attackers and privileged users. As the attacker can reach more parts of the program by tainting guards, `AttackerModelInfoflow` and `ReachableByAttacker` need to be mutually recursive (via the intermediate `TaintedFlow`) in order to model composite violations soundly. `Infoflow` abstracts away most of the complexity of handling a full language, including inter-procedural flow and data structures. Most of the vulnerability patterns are then expressed in terms of `TaintedFlow`, which is a transitive closure on `AttackerModelInfoflow`.

6 Evaluation

This section presents the results of our evaluation of the Ethainter analysis. We ran the analysis using 45 concurrent analysis processes on an idle machine with two Intel Xeon E5-2687W v4 3.00GHz CPUs (each with 12 cores x 2 hardware threads, for a total of 48 hardware threads) and 512GB of RAM. We use a combined cutoff of 120 seconds for decompilation and the information flow analysis step. Programs that did not finish analyzing within these cutoffs are considered to have timed out. (This is not too-sensitive a parameter: we decompile/analyze around 98% of available contracts. Doubling the cutoff time does not substantially increase this percentage.)

Our experiments aim to answer the following research questions:

- **RQ1.** Is Ethainter an effective static analysis?
  - **RQ1.A.** Is the analysis relevant? What percentage of contracts are vulnerable?
  - **RQ1.B.** Is the analysis precise, i.e., does it have a low false-positive rate?
  - **RQ1.C.** Is the precise complete, i.e., does it flag most of the vulnerable contracts?
- **RQ2.** Is our information flow analysis efficient?
- **RQ3.** Are the individual analysis components and design decisions justified?

We performed two main experiments:

1. For the *simplest* vulnerabilities reported by Ethainter ("accessible `selfdestruct`" and "tainted `selfdestruct`") we produce a completely automated exploit generator. We apply this to the most recent contracts on the Ropsten testnet to show that a large number of the flagged ones are indeed vulnerable. This is a crude experiment, without much accuracy but with great effectiveness at establishing a lower bound: the experiment shows that Ethainter is relevant in the real world, in an analysis domain where translating warnings to end-to-end vulnerabilities is very hard.
2. For *all* Ethainter-reported vulnerabilities, we collect statistics over a snapshot of the entire Ethereum mainnet (240K unique contracts), and then scrutinize further a small random sample of contracts, via manual

inspection. We report results for Ethainter and compare to probably the best-known state-of-the-art tool, Securify [35].

6.1 Experiment 1: Automated End-to-End Exploits

In many cases, Ethainter pinpoints vulnerabilities with enough precision to actually exploit them end-to-end. To demonstrate that it can do so with reasonable effectiveness, showcasing the execution of these vulnerabilities in the process, we have built a simple prototype tool called Ethainter-Kill that exploits vulnerabilities on real programs. Ethainter-Kill is fully automated—it reads Ethainter's output, connects to Ethereum nodes and proceeds to exploit a subset of vulnerabilities that are flagged by Ethainter. Currently, Ethainter-Kill supports only two vulnerabilities, which are "accessible `selfdestruct`" and, to a lesser extent, "tainted `selfdestruct`".

We deployed Ethainter-Kill on a private fork of the Ropsten Ethereum testnet.[2]

In this experiment, Ethainter was used to find vulnerabilities from smart contracts deployed in the most recent 1.2 million blocks. This yielded 4800 flagged contracts out of 882000 (0.54%). Out of these, Ethainter could pinpoint the vulnerability in 3003 contracts. (For the rest, Ethainter-Kill was unable to find a public entry point that would reach the private, Ethainter-flagged vulnerable statement.) Ethainter-Kill was called on these contracts, where it proceeded to connect to the relevant Ethereum node and call the API of the contracts which trigger a `selfdestruct` with some generated parameters. As expected, many calls resulted in an error, mostly due to the limitations of Ethainter-Kill. (Automated exploit generation is a challenging area of research, and actual exploits often require significant human ingenuity.) Ethainter-Kill also verified whether the transactions resulted in the contract actually being destroyed by analyzing the exact VM instruction trace and identifying whether the `selfdestruct` opcode was executed. In total **805** contracts (**16.7%** of warnings) were successfully destroyed in this experiment. This rate represents a lower bound of the true-positive rate. However, even such a lower bound is amply sufficient at demonstrating the effectiveness of Ethainter in a practical setting (i.e., to partly answer RQ1): identifying several hundred practical *end-to-end* exploits automatically is significant.

[2]We considered applying Ethainter-Kill directly on the public testnet. However, we were explicitly discouraged from doing so in conversations on Ethereum security forums [37]. The argument is that, although the testnets are intended for testing, many smart contracts on public test networks closely resemble smart contracts currently in production. Thus, any transactions we would perform on these networks could disclose the exploits publicly.

6.2 Experiment 2: Statistics and Manual Inspection

We evaluate the effectiveness of Ethainter by examining the percentage of contracts flagged for each vulnerability. We also select a subset of programs for manual inspection, and use this to estimate a true-positive rate for our analysis.

The percentage of flagged unique contract bytecodes (i.e., deployed contracts with the same bytecode are only counted once), over a total of 240K are shown below, per vulnerability:

Vulnerability	Percentage	ETH held
accessible `selfdestruct`	**1.2%**	2553101
tainted `selfdestruct`	**0.17%**	2176212
tainted owner variable	**1.33%**	221
unchecked tainted `staticcall`	**0.04%**	344
tainted `delegatecall`	**0.17%**	517

Notice that the unchecked tainted `staticcall` vulnerability is relatively rare. However, this is to be expected as it only applies to recently deployed smart contracts that utilize the new `staticcall` opcode. The number of contracts that utilize this opcode may increase in the future.

To estimate the precision (i.e., true-positive rate) of Ethainter, we randomly selected 40 contracts among those flagged by Ethainter that have verified sources on Etherscan.io (for ease of manual inspection). Contracts were repeatedly sampled randomly, after performing a lexicographical sort on their addresses (i.e., 20 byte hashes), until a random sample of 40 contracts had at least one flagged in every vulnerability category.

The results from our systematic manual inspection of the Ethainter sample are shown in Figure 6, and yield an estimated precision of **82.5%**.

In order to preserve the identity of contracts until we have a responsible disclosure agreement in place, we will refer to contracts by three hexadecimal digits contained in their identifier.

In addition to the randomly sampled contracts, Ethainter correctly flags the Parity hack [8], demonstrating its effectiveness against vulnerabilities that have led to significant losses in real-world exploits.

A certain, surprising to unfamiliar readers, aspect is worth emphasizing. The monetary amounts held by contracts flagged as vulnerable by Ethainter is currently (Mar. 2020) in the hundreds of millions of dollars. Ethainter's precision (i.e., true-positive rate) is estimated at over 80%. Does this mean that hundreds of millions can be exploited? The answer is that the actual potential for exploitation is likely dramatically lower—the distribution is strongly biased. The fact that a contract contains substantial ETH is typically strong evidence that it is not exploitable.[3] Accordingly, Pérez and

[3]Most high-value smart contracts are very carefully developed (and often audited) programs. The Ethereum blockchain holds high value precisely because costly vulnerabilities are statistically very rare (though still enough for plentiful anecdotes). Automated tools, such as ours, yield highest benefit

Contracts	Remark
Accessible `selfdestruct`. True positives: 10/10	
`6fd`✓, `9d0`✓	Poor design
`14f`✓, `342`✓, `4ea`✓	Programming error
`292`☆✓, `4fa`☆✓	Ownership guard can be tainted
`a33`	Race condition
`adf`☆✓, `d4f`☆✓	Ownership guard can be "bought"
Tainted `selfdestruct`. True positives: 6/6	
`292`☆✓, `4fa`☆✓, `d4f`☆✓	Tainted via ownership
`adf`✓	Programming error
`6fd`✓, `9d0`✓	Poor design
Tainted Owner Variable. True positives: 15/21	
`169`✓	Token supply can be manipulated
`135`✓, `26a`✓, `292`✓	-
`2cc`✓, `3a2`✓, `adf`✓	-
`4d9`✓	Conflated ownership of token&contract
`600`✓, `6c3`✓, `96b`✓	Public initializer (race condition)
`6fd`✓, `9d0`✓	Poor design
`aa4`✓, `d4f`✓	Via payment
`fc5`✗`124`✗	Complex path condition
`373`✗, `fc3`✗	Not an owner variable
`577`✗	Bug in inter-function flow
`c5c`✗	Imprecise data structure inference
Tainted `delegatecall`. True positives: 1/1	
`ef0`✓	Via complex flow through array
Unchecked Tainted `staticcall`. True positives: 1/2	
`8c0`✓	Missing return data size check
`152`✗	Complex memory conditions
Total Precision: 82.5% (33/40)	

Figure 6. Summary of results of manually inspected warnings for Ethainter. Contract ids are a 12-bit substring of their true address. Ids marked with ✗are false-positives. The ones marked with ✓are true positives. Moreover, ones marked with ☆can only be exploited via a composite tainting vulnerability.

Livshits [29] recently report that, of the vulnerabilities reported (as "true positives") in Ethereum program analysis publications, only 0.3% (in terms of Ether value) have been exploited in the wild, strongly suggesting that the truly vulnerable contracts rarely hold ETH.

Comparison to Securify. We continue to answer RQ1.B by comparing against other tools. Under the same setting as our overall sampling of Ethainter vulnerability warnings, we also perform a comparison to the recent Securify [35] tool. Securify implements two "violation patterns" that are roughly applicable to four of the vulnerabilities described in Section 3.

when employed during development or initial deployment (e.g., during a bug bounty phase). By final deployment of a contract and use with funds, most vulnerabilities have been eliminated.

To ensure a fair comparison, we only consider contracts that are flagged for vulnerabilities that have an approximate analogue supported by the other tool. For instance, Securify's "unrestricted write" pattern is similar to Ethainter's tainted owner variable vulnerability specification: it models precisely the case of owner-sender guards, but without propagation of taintedness into guards. Likewise, Securify's "missing input validation" pattern corresponds approximately to Ethainter's tainted `delegatecall`/owner variable/`selfdestruct`/tainted unchecked `staticcall`.[4] Since Securify is capable of flagging both "violations" and "warnings", we consider only "violations", as these are the most likely to be true positives.

Just as for Ethainter, we select 40 Securify-flagged contracts at random for manual inspection. (We ran Securify over a random sample of 2K contracts instead of on all 240K contracts of our dataset.)

We find that *none* of the 40 Securify-flagged contracts are truly vulnerable, giving Securify a precision (i.e., true-positive rate) of **0%**. Note that although the Securify paper [35] appears to report a much higher precision, its definition of a "true violation" is the violation of a *security property* rather than the existence of an apparent end-to-end *exploitable* vulnerability. Still, our experimental results initially looked surprising, so we further investigated this lack of precision. Firstly, this result is due to Securify's lack of support for context sensitivity, data structure modeling, ownership guards and their tainting. In our random sample of 2K contracts, Securify flags a very high **39.2%** for these violations, so a low precision for end-to-end vulnerabilities should not be surprising. Securify generally flags 75% of all contracts for *some* violation, with 10 or more violations per flagged contract.

For instance, a typical contract we inspected that would be severely flagged by Securify with "unrestricted write" or "missing input validation" would contain logic such as this:

```
if (balances[_from] < _value ||
    allowed[_from][msg.sender] < _value) throw;
balances[_to] += _value;
balances[_from] -= _value;
```

In this case: (i) the condition that checks for underflows is not understood (hence a "missing input validation") and (ii) the maps (e.g., `balances`) are not modeled as high-level data structures (the compiled code contains only pointer

[4]The pattern is somewhat different, but its code (https://github.com/eth-sri/securify/blob/master/src/main/java/ch/securify/patterns/MissingInputValidation.java) shows it to be an analysis with a very similar purpose, namely to find tainted input propagation. Lines 45-84 search for inputs that do not flow to a guard (`JUMPI`), yet flow to an `SSTORE`, `SLOAD`, `MLOAD`, `MSTORE`, `HASH`, or `CALL`.

arithmetic), and hence the store gets interpreted as an "unrestricted write".

Comparison to Securify v2.0. In late Jan. 2020, the second version of Securify was released, dubbed Securify2 [**?**] and superseding the original. Securify2 boasts several precision improvements—e.g., context-sensitive analyses.

As the successor of a directly-comparable, industry-leading tool, Securify2 is a good comparison target for Ethainter, in the context of RQ1.B. However, it should be emphasized that design-wise the tool has diverged significantly from the original Securify. Most notably, Securify2 is a source-code-only analysis, not an analysis over EVM bytecode. This means that the domain of the tool is very different from that of Ethainter (and of the original Securify). Securify2 supports smart contracts written in the Solidity language, versions 0.5.8+. Currently (mid-March 2020) the Etherscan blockchain explorer reports 6,472 unique contract bytecodes compiled with Solidity 0.5.8+, over a total of 262,812 unique contract codes. If we consider all contracts with source code on Etherscan that successfully compile with Solidity 0.5.8 (even if they were compiled with other versions when deployed), we get a slightly larger set of 7,276 contracts, which is still a minuscule part (under **3%**) of the domain of applicability of Ethainter (and of the original Securify tool). Of these 7,276 contracts, Securify2 fails to produce analysis input facts for 1,182 and times our on another 441. We consider the 7,276 - 1,182 = 6,094 contracts as the universe of our evaluation, so that we can also measure relative timeout rates.

Over these 6,094 contracts, we examine the closest comparable vulnerabilities reported by both Ethainter and Securify2. We consider Securify2 reports that are tagged as "violations" (i.e., the most precise, highest-confidence, analysis). The table in Figure 7 shows the number of reports and failures-to-analyze for both tools, as well as result of manual inspection of the warnings.

The design differences of the tools are evident: Securify2 reports few vulnerabilities for accessible `selfdestruct` and tainted `delegatecall` (patterns named "UnrestrictedSelfdestruct" and "UnrestrictedDelegateCall" in Securify2). Ethainter reports largely the same vulnerabilities (4-of-5 and 2-of-3 of the Securify2 ones), but also many more, with high precision (**70%** over all 46 manually-inspected contracts). Securify2 does exhibit high precision for its accessible `selfdestruct` warnings but zero precision for tainted `delegatecall`. (It also exhibits very low completeness for tainted `delegatecall` because the buggy pattern typically appears in inline EVM assembly, which a source-only tool cannot handle.)

Furthermore, Securify2 has no definition of tainted owner variable, which is a key novelty of Ethainter (see discussion in Section 4.5). The closest comparable is the "unrestricted write" violation, which is, however, much more loose (as it also was in the original Securify). Over a sample of 10, none of the reported Securify2 violations for "unrestricted write" corresponds to a real vulnerability. (The overall number of 3,502 reports also suggests very high imprecision.)

The result shows vividly the effect of Ethainter's design decisions over both the completeness and the precision of the analysis: Ethainter finds many more vulnerabilities, with high precision.

Comparison to teEther. We answer question RQ1.C (completeness) by comparing against teEther [22]: a third party symbolic execution tool that is designed to exploit some of the vulnerabilites that Ethainter is designed to flag—accessible `selfdestruct` and tainted `selfdestruct`. This is a **highly-instructive comparison since it pits a static analysis tool agains a symbolic execution tool**. Both approaches have been used extensively in the blockchain space, but, to our knowledge, no direct comparison of representatives exist in the literature.

Generally, the expectation would be that a static analysis approach is much more complete (issuing many more warnings) but the symbolic execution approach is more precise, since the vulnerabilities are nearly dynamically exercised. That is, teEther's reports are expected to be (mostly) true positives and Ethainter should find most of them if it is to claim good completeness (i.e., few false negatives). However, this is only an approximate gauge to measure completeness: teEther is also neither sound nor precise. It may be considered incomplete simply by virtue that it scales only to a fraction of the contracts deployed, and this incompleteness may introduce bias. It is also imprecise as it does not take into consideration the current state of the deployed smart contract (many of the exploits can only be executed under the right conditions, e.g., uninitialized owner variables). Despite this, the fact that it actually produces exact execution traces that demonstrate the viability of the exploit means that it should be, by design, a tool that finds a larger percentage of realizable exploits (though a much smaller overall number).

On our entire dataset, teEther flags 641 contracts for accessible `selfdestruct`. Out of these, Ethainter flags 509 contracts (**81%**). This is a good indication of Ethainter's completeness—or at least that it does not miss most of the warnings of an expected-to-be more precise tool. As discussed, even the 81% figure is not an accurate upper bound of completeness (i.e., 19% is not guaranteed to be an accurate estimate of false negatives) since teEther's reports may also include false positives that Ethainter's analysis eliminates.

Conversely, teEther's completeness is low: on 20 hand-checked contracts flagged by Ethainter, teEther does not flag any. It fails to report a vulnerability for 13, times out on 5 after 120s, and exits with an exception for 2. Overall, Ethainter flags many times more contracts than teEther (in the thousands—e.g., close to 3,000, as opposed to 641 for

Vulnerability/Outcome	Securify2		Ethainter	
Timeout (at 120sec)	441		138	
accessible `selfdestruct`	5	True positives: 5/5	15	True positives: 11/15
tainted owner var. / unr. write	3502	True positives (sampled): 0/10	161	True positives (sampled): 6/10
tainted `delegatecall`	3	True positives: 0/3	21	True positives: 15/21

Figure 7. Results of comparison (including manual inspection) with Securify2, over 6,094 total contracts.

accessible `selfdestruct`) and does so with high precision, as shown earlier.

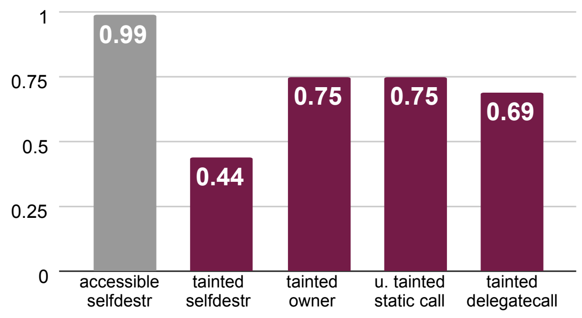
Research Question 1: Summary. The above experiment completes the picture on RQ1: Ethainter is an effective static analysis, practically relevant, flagging a usefully large number of contracts, with high precision and completeness.

6.3 Efficiency of Analysis

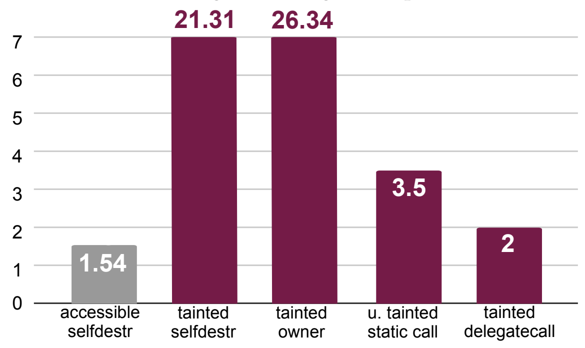
Ethainter is a highly efficient analysis (answering RQ2 positively). It analyzes all 240K non-duplicate contracts on the blockchain, corresponding to a total of 38 million lines of 3-address code, in 6 hours (or about 200 CPU hours, given our concurrency factor of 45, plus overheads). The average analysis runtime per contract (including decompilation) is under 5 seconds. It is informative to compare the scalability of our analysis to well known research tools for the Ethereum space, such as Oyente [25], which produces average runtimes of 350 seconds with some contracts timing out after a cutoff of 60 minutes [25]. Similarly, Securify analyzes contracts over 5x more slowly than (single-thread) Ethainter (this is a lower bound since the exact number depends on how one counts timeouts, which are more numerous for Securify) and is not parallelizable in its current form, due to its use of shared resources (e.g., temporary file). The scalability improvement is also apparent even over state-of-the-art tools such as MadMax [13], which report analysis times of 10 hours for a much smaller version of the Ethereum blockchain (92K contracts).

6.4 Design Decisions

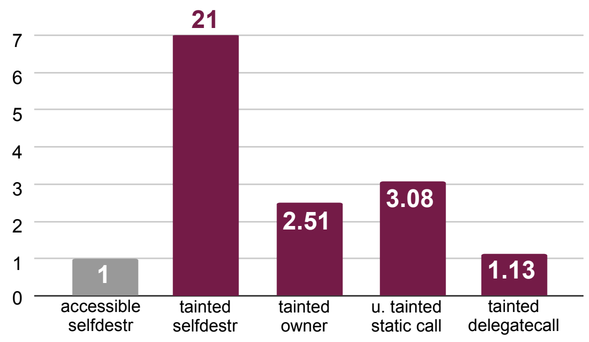
RQ3 concerns the effectiveness of the analysis under different design decisions. Ethainter optimizes for precision by modeling source language features and application design patterns that can help distinguish whether a vulnerability is likely real. One feature in which we have invested significant design effort is the realistic modeling of guards. Figure 8b shows that if we disregard the modeling of guards while keeping all other design choices constant (i.e., 'No Guard Model'), the percentage of unique programs that are flagged as vulnerable by Ethainter increases drastically. The newly flagged contracts are (overwhelmingly, if not exclusively) false positives. The increase in flagged contracts (and hence false-positive rate) is most pronounced for the "tainted `selfdestruct`" vulnerability. This is because oftentimes contracts are designed to take an address as a parameter to the public function that



(a) No Storage Modeling (↓ completeness)



(b) No Guard Modeling (↓ precision)



(c) Conservative Storage Modeling (↓ precision)

Figure 8. Effect of analysis design decisions: number of analysis reports, normalized to default analysis. Chart 8a shows reduced completeness (fewer reports), Charts 8b and 8c show reduced precision. (Disclosure: due to a technical glitch, reports for "accessible selfdestruct", shown gray, are for an earlier version of our experiments than the rest.)

calls `selfdestruct`, to transfer the remaining balance of the contract to this address. The Ethainter design recognizes this, and, since the `selfdestruct` is usually guarded and the taint cannot be transferred from unguarded to guarded portions of the program, the modeling is precise.

On the other hand, if we do not allow taint to propagate via storage (and hence across multiple transactions, as is needed to execute some of the exploits that were checked manually), we obtain a sizable reduction in flagged contracts due to *incompleteness* introduced (Figure 8a). Notice that the reduction in flagged contracts is most pronounced also for the "tainted `selfdestruct`" vulnerability, since many of these exploits require overriding a guard (by overwriting an owner variable, residing in storage). Note that systems that employ symbolic execution, such as Oyente [25], tend not to consider value flow across multiple transactions.

Some of the design decisions we have taken also sacrifice some of the completeness of Ethainter. If we attempt to model imprecisely but completely (much like the Securify tool does [35]—Fig.8, non-const memory rules) storage locations that cannot be resolved as being part of a data structure or have a known constant address, we get an unacceptable decrease in precision, as shown in Figure 8c. The conservative modeling assumes that any store to an unknown location in storage can propagate to any location in storage, and the converse for loads. The false-positive rate for several vulnerabilities (e.g., "tainted `selfdestruct`", "tainted owner variable") becomes significantly higher as a result.

7 Related Work

Recent security issues in smart contracts have spawned a strong interest for analysis and verification in the community, with a rapidly growing number of papers.

Our approach is a static analysis approach and analyzes EVM bytecode, modeling data structures, notions of ownership, and notions of tainted information flow. Information flow has received a lot of attention starting with the seminal work of Denning and Denning [11], which introduced a compile-time mechanism for certifying programs as secure with respect to information flow properties. Later works have introduced important extensions to information flow [31]. Taint analysis (e.g., [2, 17]) is a simplified information flow problem that tracks the propagation of input values in a program.

Previous works for smart contracts can be categorized according to their underlying techniques, including symbolic execution, formal verification, and abstract interpretation.

Systems including Oyente [25], SASC [42], Maian [28], GASPER [7], teEther [22] and ECFChecker [16] use a symbolic execution/trace semantics approach that (compared to exhaustive static analysis) is much less complete/exhaustive, since only some program paths of smart contracts will be explored. Oyente is probably the earliest and best-known representative of such work: it checks for security vulnerabilities including transaction order dependency, timestamp dependency, and reentrancy. Maian [28] analyzes multiple invocations of a smart contract and covers safety properties including prodigality and self-destruction. TeEther [22] is a recent representative of symbolic execution tools, offering both detection of information flow-like properties and exploit generation. Although symbolic execution warnings are expected to have high precision, the goal of our work is to combine feasibly high precision and completeness.

The smart contract analysis literature also includes formal verification approaches, with more emphasis on deep modeling and less on automatic analysis. The Zeus framework [21] translates Solidity source code to LLVM bitcode [24] before performing the actual analysis in the SeaHorn verification framework [32]. This approach however fails to abstract all Solidity instructions and the EVM execution platform correctly. An alternative approach [26] abstracts Solidity code to finite-state automata. EtherTrust [15] is a sound static modeling tool using a small-step semantics. EtherTrust analyzes EVM bytecode directly for single-entrancy vulnerabilities, using Z3 as an underlying SMT solver.

Rodler et al. [30] present an interesting approach for protecting contracts vulnerable to reentrancy vulnerabilities, instead of merely detecting such vulnerabilities. Interestingly, they confirm (for an attack domain different from our information flow vulnerabilities) that Securify employs "very conservative violation pattern[s] ..., which consequently results in a very high false-positive rate."

Other tools [18, 19, 36] employ fuzzing techniques in order to detect various vulnerabilities. The recent ILF [18] tool trains a neural network using inputs generated by symbolic execution in order to increase fuzzing effectiveness.

Various exploits have been broadly identified in the literature [3, 4, 10, 33]: exploits related to Solidity, the EVM and the blockchain itself. These exploits have been highlighted by the community outside of publications. For instance, the security company Consensys maintains a website [9] outlining the exploits mentioned in the literature, as well as additional exploits, such as data overflows and underflows, and suggestions on how to write better smart contracts (such as isolating external calls into their own transactions, instead of executing them in a single transaction, to minimize the risk of failures and side effects).

Finally, taint analysis tools for other domains are in abundance and some have used Datalog, as in our work. Livshits [23] has fruitfully explored the use of Datalog for taint analysis in Java. P/Taint [14] is a recent declaratively specified unified taint and pointer analysis framework for both Java and Android. Its implementation methodology allows full-featured context-sensitive taint analysis frameworks to emerge out of existing pointer analysis frameworks at little additional implementation and runtime cost.

8 Conclusions

We presented the Ethainter security analyzer for detecting composite vulnerabilities in smart contracts. Ethainter employs notions of information flow for tracking tainted values, while extending them to model key concepts for the domain, such as sanitization via guards and taint through persistent storage. We give a specification of the analysis in a distilled formalism, likely of independent value. We identify practical information flow vulnerabilities in the full Ethereum blockchain, e.g., introduce taint to bypass an ownership guard to destroy the contract. The analysis is finely tuned for precision and scalability. Ethainter identifies real security issues in deployed contracts, all the way to automatic exploitation of hundreds of contracts on the Ropsten test network.

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