

# The Eye of Horus: Spotting and Analyzing Attacks on Ethereum Smart Contracts

Christof Ferreira Torres<sup>1</sup>, Antonio Iannillo<sup>1</sup>, Arthur Gervais<sup>2</sup>, and Radu State<sup>1</sup>

<sup>1</sup> SnT, University of Luxembourg

<sup>2</sup> Imperial College London

**Abstract.** In recent years, Ethereum gained tremendously in popularity, growing from a daily transaction average of 10K in January 2016 to an average of 500K in January 2020. Similarly, smart contracts began to carry more value, making them appealing targets for attackers. As a result, they started to become victims of attacks, costing millions of dollars. In response to these attacks, both academia and industry proposed a plethora of tools to scan smart contracts for vulnerabilities before deploying them on the blockchain. However, most of these tools solely focus on detecting vulnerabilities and not attacks, let alone quantifying or tracing the number of stolen assets. In this paper, we present HORUS, a framework that empowers the automated detection and investigation of smart contract attacks based on logic-driven and graph-driven analysis of transactions. HORUS provides quick means to quantify and trace the flow of stolen assets across the Ethereum blockchain. We perform a large-scale analysis of all the smart contracts deployed on Ethereum until May 2020. We identified 1,888 attacked smart contracts and 8,095 adversarial transactions in the wild. Our investigation shows that the number of attacks did not necessarily decrease over the past few years, but for some vulnerabilities remained constant. Finally, we also demonstrate the practicality of our framework via an in-depth analysis on the recent Uniswap and Lendf.me attacks.

**Keywords:** Ethereum · Smart Contracts · Attack Detection · Forensics.

## 1 Introduction

As of today, Ethereum [47] revolutionized the way digital assets are traded by being the first to introduce the concept of Turing-complete smart contracts on the blockchain. These are programs that are executed and stored across the blockchain. However, due to the tamper-resistant nature of blockchains, smart contracts can no longer be modified once deployed. At the time of writing, Ethereum has a market capitalization of over 42 billion USD, making it the second most valuable cryptocurrency on the market [4]. As of writing, WETH, the most valuable Ethereum smart contract holds more than 2 billion USD worth of ether (Ethereum’s own cryptocurrency) [13]. Moreover, Ethereum grew in the past 4 years from a daily transaction average of 10K in January 2016 to an average of 500K in January 2020 [12]. Such an increase in value and popularity

attracts abuse and the lack of a governing authority has led to a “Wild West”-like situation, where several attackers began to exploit vulnerable smart contracts to steal their funds. In the past, several smart contracts hosting tens of millions of USD were victims to attacks (e.g., [24, 50, 35]). Hence, over the past few years a rich corpus of research works and tools have surfaced to identify smart contract vulnerabilities (e.g., [26, 44, 15, 29, 43, 2, 18, 21, 23]). However, most of these tools only focus on analyzing the bytecode of smart contracts and not their transactions or activities. Only a small number leverages transactions to detect attacks (e.g., [36, 3, 48]), whereas the majority either requires the Ethereum client to be modified or large and complex attack detection scripts to be written. Moreover, none of these tools allow to directly trace stolen assets after their detection.

In this work, we introduce HORUS, a framework capable of automatically detecting and analyzing smart contract attacks from historical blockchain data. Besides detecting attacks, the framework also provides means to quantify and trace the flow of stolen assets across Ethereum accounts. The framework replays transactions without modifying the Ethereum client and encodes their execution as logical facts. Attacks are then detected using Datalog queries, making the framework easily extendable to detect new attacks. Stolen funds are traced by loading detected transactions into a graph database and performing transaction graph analysis. Using our framework, we conduct a longitudinal study that spans the entire past Ethereum blockchain history, from August 2015 to May 2020, consisting of over 3 million smart contracts. One of the fundamental research questions we are investigating is whether these years of efforts have yielded visibly fewer attacks in the wild. If the tools proposed herein are effective, one could argue that attacks should have declined over time. To quantify the answer to this question, we start by investigating whether attacks occur continuously, or if they appear sporadically. While most well-known attacks carry significant monetary value, we wonder whether smaller, but ongoing attacks may occur more often and remain rather occluded.

**Contributions.** We present the design and implementation of HORUS, a framework that helps identifying smart contract attacks based on a sequence of blockchain transactions using Datalog queries. In addition, the framework extracts the quantity of stolen funds, including ether as well as tokens, and traces them across accounts to support behavioral studies of attackers. We provide a longitudinal study on the security of Ethereum smart contracts of the past 4.5 years, and find 8,095 attacks in the wild, targeting a total of 1,888 vulnerable contracts. Finally, we perform a forensic analysis of the recent Uniswap and Lendf.me hacks.

The remainder of the paper is organized as follows. Section 2 introduces background on smart contracts and the Ethereum virtual machine. Section 3 presents our framework. Our evaluation is discussed in Section 4. Section 5 analyzes our results and presents our forensic analysis on the Uniswap and Lendf.me incidents. Finally, Section 6 and Section 7 discuss related work and conclude our paper, respectively.

## 2 Background

**Smart Contracts.** Although, the notion of smart contracts is not new [41], the concept only became wide-spread with the release of Ethereum in 2015. Ethereum smart contracts are fully-fledged programs that are different from traditional programs in several ways. They are deterministic as they must be executed across a network of mutually distrusting nodes. Once deployed, smart contracts cannot be removed or updated, unless they have been explicitly designed to do so. Furthermore, every smart contract has a balance that keeps track of the amount of ether owned by the contract, and a value storage that allows to keep state across executions. They are usually developed using a high-level programming language, such as Solidity [46], that compiles into low-level bytecode. This bytecode is interpreted by the Ethereum Virtual Machine (EVM).

**Transactions.** The deployment and execution of smart contracts occurs via transactions. Smart contracts are identifiable via a unique 160-bit address that is generated during deployment. Transactions may only be initiated by externally owned accounts<sup>3</sup>. Smart contract functions are triggered by encoding the function signature and arguments in the data field of a transaction. A fallback function is executed whenever the provided function name is not implemented. Transactions may also contain a given amount of ether that shall be transferred from one account to another. Smart contracts may call other smart contracts during execution, thus, a single transaction may trigger further transactions, so-called internal transactions.

**Ethereum Virtual Machine.** The EVM is a stack-based virtual machine that supports a Turing-complete set of instructions allowing smart contracts to store data and interact with the blockchain. The EVM uses a gas mechanism to associate costs to the execution of instructions. This guarantees termination and prevents denial-of-service attacks. The EVM holds a machine state  $\mu = (g, pc, m, i, s)$  during execution, where  $g$  is the gas available,  $pc$  is the program counter,  $m$  represents the memory contents,  $i$  is the active number of words in memory, and  $s$  is the content of the stack.

## 3 The Horus Framework

In this section, we provide details on the design and implementation of the HORUS framework. HORUS automates the process of conducting longitudinal studies of attacks on Ethereum smart contracts. The framework has the capability to detect and analyze smart contract attacks from historical data. Moreover, the framework also provides means to trace the flow of stolen assets across Ethereum accounts. The latter is particularly useful for studying the behavior of attackers. Fig. 1 provides an overview on the architecture of HORUS. The framework is organized as an EAT (extract, analyse, and trace) pipeline consisting of three different stages:

<sup>3</sup> Externally owned accounts are accounts controlled via private keys that have no associated code.

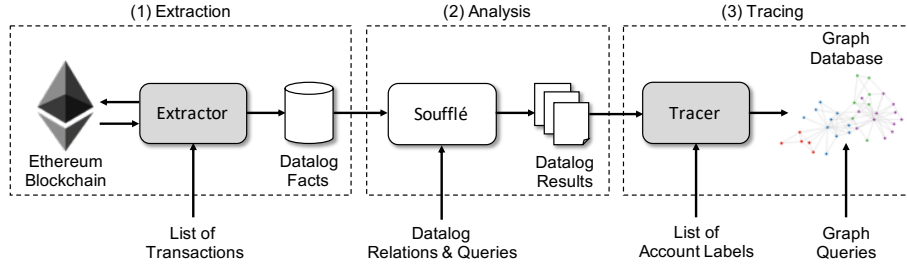


Fig. 1: Architecture of HORUS. Shaded boxes represent custom components, whereas boxes highlighted in white represent off-the-shelf components.

- (1) **Extraction:** The extraction stage takes as input a list of transactions from which execution related information is extracted and stored as Datalog facts.
- (2) **Analysis:** The analysis stage takes as input a set of Datalog relations and queries, which together identify attacks on the extracted Datalog facts.
- (3) **Tracing:** The tracing stage retrieves a list of attacker accounts obtained via the analysis and fetches all transactions related to these accounts (including normal transactions, internal transactions and token transfers). Afterwards, a graph database is created, which captures the flow of funds (both ether and tokens) from and to these accounts. Further, the database can be augmented with a list of labeled accounts to enhance the tracing of stolen assets.

In the following, we describe each of the three pipeline stages in more detail. The entire framework was written in Python using roughly 2,000 lines of code<sup>4</sup>.

### 3.1 Extraction

The role of the extractor is to request from the Ethereum client the execution trace for a list of transactions and to convert them into logic relations that reflect the semantics of their execution. An execution trace consists of an ordered list of executed EVM instructions. Each record in that list contains information such as the executed opcode, program counter, call stack depth, and current stack values. Unfortunately, execution traces cannot be obtained directly from historical blockchain data, they can only be recorded during contract execution. Fortunately, the Go based Ethereum client (Geth) provides a debug functionality via the `debug_traceTransaction` and `debug_traceBlockByNumber` functions, which gives us the ability to replay the execution of any given past transaction or block and retrieve its execution trace. Execution traces are requested via Remote Procedure Call (RPC). Previous works [36, 34, 3, 49, 48], did not rely on RPC as it is too slow. Instead, they modified Geth to speed up the process of retrieving execution traces. However, this has the limitation that users cannot use Geth’s default version, but are required to use a modified version, and changes will need to be carried over every time a new version of Geth is released. Moreover, at

<sup>4</sup> Code and data are publicly available at <https://github.com/christoftorres/Horus>.

the time of writing, none of these works publicly disclosed their modified version of Geth, which not only makes it difficult to reproduce their results, but also to conduct future studies. Therefore, rather than modifying Geth, we decided to improve the speed on the retrieval of execution traces via RPC. We noticed that execution traces contain a number of information that is irrelevant for our analysis. Fortunately, Geth allows us to inject our own execution tracer written in JavaScript [42]. Through this mechanism, we are able to reduce the size of the execution traces and improve execution speed, without actually modifying Geth. For example, our JavaScript code removes the current program counter, the remaining gas and the instruction’s gas cost from the execution trace. Moreover, instead of returning a complete snapshot of the entire stack and memory for every executed instruction, our code only returns stack elements and memory slices that are relevant to the executed instruction.

```
.decl opcode(step:number, op:Opcode, tx_hash:symbol)
.decl data_flow(step1:number, step2:number, tx_hash:symbol)
.decl arithmetic(step:number, op:Opcode, operand1:Value, operand2:Value,
  arithmetic_result:Value, evm_result:Value)
.decl storage(step:number, op:Opcode, tx_hash:symbol, caller:Address,
  contract:Address, index:Value, value:Value, depth:number)
.decl condition(step:number, tx_hash:symbol)
.decl erc20_transfer(step:number, tx_hash:symbol, contract:Address, from:
  Address, to:Address, value:Value)
.decl call(step:number, tx_hash:symbol, op:Opcode, caller:Address, callee
  :Address, input:symbol, value:Value, depth:number, call_id:number,
  call_branch:number, result:number)
.decl selfdestruct(step:number, tx_hash:symbol, caller:Address, contract:
  Address, destination:Address, value:Value)
.decl block(block_number:number, gas_used:number, gas_limit:number,
  timestamp:number)
.decl transaction(tx_hash:symbol, tx_index:number, block_number:number,
  from:Address, to:Address, input:symbol, gas_used:number, gas_limit:
  number, status:number)
```

Listing 1: List of Datalog facts extracted by HORUS.

Listing 1 shows the list of Datalog facts that our extractor produces by iterating through each of the records of the execution traces and encoding relevant information. While most facts are related to low level EVM operations (e.g., `call`), others are related to high level operations. For example, the `erc20_transfer` fact refers to the ERC-20 token event “Transfer” that is emitted whenever tokens are transferred, where `contract` denotes the address of the token contract, and `from` and `to`, denote the sender and receiver of the tokens, respectively. It is important to note that this list can easily be modified or extended to support different studies from the one proposed in this paper by modifying the extractor, analyzer and tracer. Besides using the default types `number` and `symbol`, we also define our own three new types: `Address` for 160-bit values, `Opcode` for the set of EVM opcodes, and `Value` for 256-bit stack values.

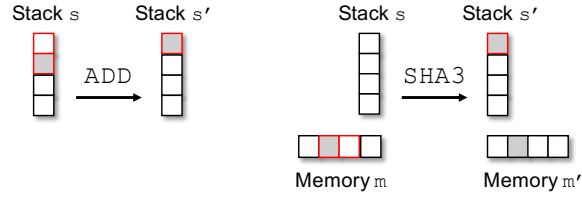


Fig. 2: The example on the left depicts the propagation of taint via the **ADD** instruction, where the result pushed onto stack  $s'$  becomes tainted because the second operand on stack  $s$  was tainted. The example on the right depicts the propagation of taint via the **SHA3** instruction, where the result pushed onto stack  $s'$  becomes tainted because the memory  $m$  was tainted.

**Dynamic Taint Analysis.** The extractor leverages dynamic taint analysis to track the flow of data across instructions. Security experts can then use the `data_flow` fact to check if data flows from one instruction to another. Taint is introduced via sources, then propagated across the execution and finally checked if it flows into sinks. Sources represent instructions that might introduce untrusted data (e.g., `CALLDATALOAD` or `CALLDATACOPY`), whereas sinks represent instructions that are sensitive locations (e.g., `CALL` or `SSTORE`). We implemented our own dynamic taint analysis engine. The engine loops through every executed instruction and checks whether the executed instruction is a source, for which the engine then introduces taint by tagging the affected stack value, memory region or storage location according to the semantics defined in [47]. We implemented the stack using an array structure following LIFO logic. Memory and storage are implemented using a Python dictionary that maps memory and storage addresses to values. Taint propagation is performed at the byte level (see examples in Fig. 2).

**Execution Order.** Attacks such as the Parity wallets hacks were composed of two transactions being executed in a specific order. To detect such multi-transactional attacks, our framework encodes a total order across multiple transactions via the triplet  $o = (b, t, s)$ , where  $b$  is the block number,  $t$  is the transaction index, and  $s$  is the execution step. The execution step is a simple counter that is reset at the beginning of the execution of a transaction and its value is incremented after each executed instruction. An execution step is bound to a transaction index, which is on the other hand bound to a block number. As such, our framework is able to precisely identify the execution order of any instruction across multiple transactions and the entire blockchain history.

### 3.2 Analysis

The second stage of our pipeline uses a Datalog engine to analyze whether a given list of Datalog relations and queries match any of the previously extracted Datalog facts. These Datalog queries identify adversarial transactions, i.e., malicious transactions that successfully carried out a concrete attack against a smart

contract by exploiting a given vulnerability. Our framework uses Soufflé as its Datalog engine. Soufflé compiles Datalog relations and queries into a highly optimized C++ executable [22]. In the following, we provide Datalog queries for detecting reentrancy, Parity wallet hacks, integer overflows, unhandled exceptions and short address attacks. Although, a number of smart contract vulnerabilities exist [1], in this work we focus on those that are ranked by the NCC Group as the top 10 smart contract vulnerabilities [30] and for which we can extract the amount of ether or tokens that were either stolen or locked.

**Reentrancy.** Reentrancy occurs whenever a contract calls another contract, and the called contract calls back the original contract (i.e., a re-entrant call) before the state in the original contract has been updated appropriately. We detect reentrancy by identifying cyclic calls originating from the same caller and calling the same callee (see Listing 2). We check if two successful `calls` (i.e., result is 1), share the same transaction `hash`, `caller`, `callee`, `id` and `branch`, where the second call has a higher call `depth` than the first call. Afterwards, we check if there are two `storage` operations with the same call depth as the first call, where the first operation is an `SLOAD` and occurs before the first call, and the second operation is an `SSTORE` and occurs after the second call.

```
Reentrancy(hash, caller, callee, depth2, amount) :-
  storage(step1, "SLOAD", hash, _, caller, index, _, depth1),
  call(step2, hash, _, caller, callee, _, _, depth1, id, branch, 1),
  call(step3, hash, _, caller, callee, _, amount, depth2, id, branch, 1),
  storage(step4, "SSTORE", hash, _, caller, index, _, depth1),
  depth1 < depth2, step1 < step2, step3 < step4, !match("0", amount).
```

Listing 2: Datalog query for detecting reentrancy attacks.

**Parity Wallet Hacks.** In this paper, we focus on detecting the two Parity wallet hacks [50, 35]. Both hacks were due faulty access control implementations that allowed attackers to set themselves as owners, which allowed them to perform critical actions such as the transfer of funds or the destruction of contracts. We detect the first Parity wallet hack by checking if there exist two `transactions`  $t_1$  and  $t_2$ , both containing the same sender and receiver, where the first 4 bytes of  $t_1$ 's input match the function signature of the `initWallet` function (i.e., `e46dcfeb`), and if the first 4 bytes of  $t_2$ 's input match the function signature of the `execute` function (i.e., `b61d27f6`) (see Listing 3). Afterwards, we check whether there is a `call`, which is part of  $t_2$  and where  $t_2$  is executed after  $t_1$  (i.e., `block1 < block2`; `block1 = block2`, `index1 < index2`).

```
ParityWalletHack1(hash1, hash2, caller, callee, amount) :-
  transaction(hash1, index1, block1, from, to, input1, _, _, 1),
  substr(input1, 0, 8) = "e46dcfeb",
  transaction(hash2, index2, block2, from, to, input2, _, _, 1),
  substr(input2, 0, 8) = "b61d27f6",
  call(_, hash2, "CALL", caller, callee, _, amount, _, 1),
  (block1 < block2; block1 = block2, index1 < index2).
```

Listing 3: Datalog query for detecting the first Parity wallet hack.

We detect the second Parity wallet hack in a very similar way to the first one, except that in this case we check if  $t_2$ 's input matches the function signature of the `kill` function (i.e., `cbf0b0c0`) and  $t_2$  contains a `selfdestruct` (see Listing 4).

```
ParityWalletHack2(hash1, hash2, contract, destination, amount) :-
  transaction(hash1, index1, block1, from, to, input1, _, _, 1),
  substr(input1, 0, 8) = "e46dcfeb",
  transaction(hash2, index2, block2, from, to, input2, _, _, 1),
  substr(input2, 0, 8) = "cbf0b0c0",
  selfdestruct(_, hash2, _, contract, destination, amount),
  (block1 < block2; block1 = block2, index1 < index2).
```

Listing 4: Datalog query for detecting the second Parity wallet hack.

**Integer Overflows.** We detect integer overflows by checking if data from `CALLDATALOAD` or `CALLDATACOPY` `opcodes` flows into an `arithmetic` operation, where the arithmetic result does not match the result returned by the EVM. Afterwards, we check whether the result of the arithmetic operation flows into an `SSTORE` `storage` operation and an `erc20.transfer` occurs, where the `amount` is one of the two operands used in the arithmetic computation (see Listing 5). Please note that in this work, we only focus on detecting integer overflows related to ERC-20 tokens, since token smart contracts have been identified in the past to be frequent victims of integer overflows [32, 33].

```
IntegerOverflow(hash, from, to, amount) :-
  (opcode(step1, "CALLDATALOAD", hash);
   opcode(step1, "CALLDATACOPY", hash)),
  arithmetic(step2, _, operand1, operand2, arithmetic_res, evm_res),
  arithmetic_res != evm_res, (operand1 = amount; operand2 = amount),
  storage(step3, "SSTORE", hash, _, _, _, 1),
  data_flow(step1, step2, hash), data_flow(step2, step3, hash),
  erc20_transfer(_, hash, _, from, to, amount), !match("0", amount).
```

Listing 5: Datalog query for detecting integer overflow attacks.

**Unhandled Exception.** Inner calls executed by smart contracts may fail and by default only the state changes caused by those failed calls are rolled back. It is the responsibility of the developer to check the result of every call and perform proper exception handling. However, many developers forget or decide to ignore the handling of such exceptions, resulting in funds not being transferred to their rightful owners. We detect an unhandled exception by checking whether a `call` with opcode `"CALL"` failed (i.e., result is 0) with an `amount` larger than zero and where the result was not used in a `condition` (see Listing 6).

```
UnhandledException(hash, caller, callee, amount) :-
  call(step, hash, "CALL", caller, callee, _, amount, _, 0),
  !match("0", amount), !used_in_condition(step, hash).
```

Listing 6: Datalog query for detecting unhandled exceptions.



**Short Address.** The ERC-20 functions `transfer` and `transferFrom` take as input a destination address and a given amount of tokens. During execution the EVM will add trailing zeros to the end of the transaction input if the transaction arguments are not correctly encoded as chunks of 32 bytes, thereby shifting the input bytes to the left by a few zeros, and therefore unwillingly increase the number of tokens to be transferred. However, attackers can exploit this fact by generating addresses that end with trailing zeros and omit these zeros, to then trick another party (e.g., web service) into making a call to `transfer/transferFrom` containing the attacker’s malformed address. We detect a short address attack by first checking if the first 4 bytes of a `transaction`’s input match either the function signature of `transfer` (i.e., `a9059cbb`) or `transferFrom` (i.e., `23b872dd`). Then, for the function `transfer` we check whether the length of the input is smaller than 68 (i.e., 4 bytes function signature, 32 bytes destination address, and 32 bytes amount), and for the function `transferFrom` we check whether the length of the input is smaller than 100 (i.e., 4 bytes function signature, 32 bytes from address, 32 bytes destination address, and 32 bytes amount), and finally we check if an `erc20_transfer` occurred (see Listing 7).

```
ShortAddress(hash, from, to, amount) :-
  transaction(hash, _, _, input, _, _, 1, _),
  (substr(input, 0, 8) = "a9059cbb", strlen(input) / 2 < 68;
   substr(input, 0, 8) = "23b872dd", strlen(input) / 2 < 100),
  erc20_transfer(_, hash, _, from, to, amount), !match("0", amount).
```

Listing 7: Datalog query for detecting short address attacks.

### 3.3 Tracing

The final stage of our pipeline is the tracing of stolen assets, such as ether and tokens, from attacker accounts to labeled accounts (e.g., exchanges). The tracer starts by extracting sender addresses and timestamps from malicious transactions that have been identified via the Datalog analysis. Sender addresses are assumed to be accounts belonging to attackers. Afterwards, the tracer uses Etherscan’s API to retrieve for each sender address all its normal transactions, internal transactions and token transfers, and loads them into a Neo4j graph database. We rely on a third-party service such as Etherscan to retrieve normal transactions, internal transactions and token transfers, because a default Ethereum node does not provide this functionality out-of-the-box. Accounts are encoded as vertices and transactions as directed edges between those vertices. We differentiate between three types of accounts: attacker accounts, unlabeled accounts, and labeled accounts. Every account type contains an address. Labeled accounts contain a category (e.g., exchange) and a label (e.g., Kraken 1). We obtain categories and labels from Etherscan’s large collection of labeled accounts<sup>5</sup>. We downloaded a total of 5,437 labels belonging to 204 categories. We differentiate between three different types of transactions: normal transactions, internal

<sup>5</sup> <https://etherscan.io/labelcloud>

transactions, and token transactions. Each transaction type contains a transaction value, transaction hash, and transaction date. Token transactions contain a token name, token symbol and number of decimals. Transactions can be loaded either backwards or forwards. Loading transactions forwards allows us to track where attackers sent their stolen funds to, whereas loading transactions backwards allows us to track where attackers received their funds from. We start with the attacker’s account when loading transactions and recursively load transactions for neighboring accounts that are part of the same transaction for up to a given number of hops. We do not load transactions for accounts with more than 1,000 transactions. This is to avoid bloating the graph database with transactions from mixing services, exchanges or gambling smart contracts. Moreover, when loading transactions backwards, we only load transactions that occurred before the timestamp of the attack, whereas when loading transactions forwards, we only load transactions that occurred after the timestamp of the attack. Finally, when all transactions are loaded, security experts can query the graph database using Neo4j’s own graph query language called Cypher, to trace the flow of stolen funds. Evidently, our tracing is only effective up to a certain point, since mixing services and exchanges prevent further tracing. Nonetheless, our tracing is still useful to study whether attackers send their funds to mixers or exchanges and to identify which services are being used and to what extent.

## 4 Evaluation

In this section, we demonstrate the scalability and effectiveness of our framework by performing a large-scale analysis of the Ethereum blockchain and comparing our results to those presented in previous works.

**Dataset.** We used the Ethereum ETL framework [28] to retrieve a list of transactions for every smart contract deployed up to block 10 M. We collected a total of 697,373,206 transactions and 3,362,876 contracts. The deployment timestamps of the collected contracts range from August 7, 2015, to May 4, 2020. We filtered out contracts without transactions and removed transactions that have a gas limit of 21,000 (i.e., do not execute code). Moreover, similar to [36], we skipped all the transactions that were part of the 2016 denial-of-service attacks, as these incur high execution times [40]. After applying these filters, we ended up with a final dataset of 1,234,197 smart contracts consisting of 371,419,070 transactions. During the extraction phase, HORUS generated roughly 700GB of Datalog facts on the final dataset.

**Experimental Setup.** All experiments were conducted using a machine with 64 GB of memory and an Intel(R) Core(TM) i7-8700 CPU with 12 cores clocked at 3.2 GHz, running 64-bit Ubuntu 18.04.5 LTS. Moreover, we used Geth version 1.9.9, Soufflé version 1.7.1, and Neo4j version 4.0.3.

### 4.1 Results

Table 1 summarizes our results: we found 1,888 attacked contracts and 8,095 adversarial transactions. From these contracts, 46 were attacked using reentrancy,

Table 1: Summary of detected vulnerable contracts and adversarial transactions.

Vulnerability	Results		Validation		
	Contracts	Transactions	TP	FP	$p$
Reentrancy	46	2,508	45	1	0.97
Parity Wallet Hacks	600	1,852	600	0	1.00
Parity Wallet Hack 1	596	1,632	596	0	1.00
Parity Wallet Hack 2	238	238	238	0	1.00
Integer Overflow	125	443	65	0	1.00
Overflow ( <i>Addition</i> )	37	139	25	0	1.00
Overflow ( <i>Multiplication</i> )	23	120	20	0	1.00
Underflow ( <i>Subtraction</i> )	104	352	68	0	1.00
Unhandled Exception	1,068	3,100	100	0	1.00
Short Address	55	275	5	0	1.00
Total Unique	1,888	8,095			

600 were attacked during the Parity wallet hacks, 125 were attacked via integer overflows, 1,068 suffered from unhandled exceptions, and 55 were victims of short address attacks. For the Parity wallet hacks, we find that the majority was attacked during the first hack. We also observe that most contracts that are vulnerable to integer overflows, were attacked via an integer underflow.

## 4.2 Validation

We confirm our framework’s correctness, by comparing our findings to those reported by previous works for which results were publicly available. Also, we solely compare our finding to works that similarly to HORUS, focus on detecting attacks rather than vulnerable contracts. In cases where the results were not publicly available, we manually inspected the source code and transactions of flagged contracts using Etherscan. Table 1 summarizes the results of our validation in terms of true positives (TP), false positives (FP) and precision ( $p$ ). Overall our framework achieves a high precision of 99.54%.

**Reentrancy.** First, we compare our results to those of SEREUM [36]. The authors reported a total of 16 vulnerable contracts, where 14 are false positives. The true positives include the DAO [6] and the DSEthToken [8] contract, which HORUS has also identified. HORUS has flagged none of the 14 false positives. Next, we compare our results to ÆGIS [14, 16]. HORUS successfully detected the 7 contracts that were reported by ÆGIS. Then, we compare our results to SODA [3]. HORUS identified 25 of the 26 contracts that were flagged as true positives by SODA. We analyzed the remaining contract (0x59abb8006b30d7357869760d21b4965475198d9d) and found that it is not vulnerable to reentrancy, which is in line with what other previous works discovered [48]. For the 5 false positives reported by SODA, we detected 3 of them, where two (0xd4cd7c881f5ceece4917d856ce73f510d7d0769e and 0x72f6eca0db6811274215694129661151f97982e) are actual true positives and have been

misclassified by SODA. The other one (known as HODLWallet [9]) is indeed a false positive. Afterwards, we compare our results with those of ETHSCOPE [48]. HORUS detected 45 out of the 46 true positives reported by ETHSCOPE. The non-reported contract is the DarkDAO [7], which did not suffer from a reentrancy attack and is, therefore, a false positive. In terms of false positives, HORUS only has one in common with ETHSCOPE, namely the aforementioned HODLWallet contract. The other two false positives that ETHSCOPE reported were correctly identified as true negatives by HORUS. Finally, we compare our results with those of Zhou et al. [51]. HORUS found 22 of the 26 contracts that have been reported as true positives by Zhou et al. We inspected the remaining 4 contracts and found that they are false positives.

**Parity Wallet Hacks.** For the first Parity wallet hack, we compared our results to those reported by ÆGIS and Zhou et al. ÆGIS reported 3 contracts, which have also been found by HORUS. Next, Zhou et al. reported 622 contracts, of which HORUS found 596. We analyzed the remaining 26 contracts and found that these are false positives. After analyzing their list of transactions, we could not find evidence of the two exploiting transactions, namely `initWallet` and `execute`. For the second Parity wallet hack, we compared our results to those of ÆGIS. HORUS found 238 contracts, of which 236 were also reported by ÆGIS. The remaining two are true positives and have not been identified by ÆGIS.

**Integer Overflow.** We compared our findings to those of Zhou et al. The authors found 50 contracts, whereas we found 125 contracts. HORUS detected 49 of the 50 contracts reported by Zhou et al. We analyzed the undetected contract (0xa9a8ec071ed0ed5be571396438a046a423a0c206) and found no evidence of an integer overflow. Besides our comparison with Zhou et al., we also tried to analyze manually the source code of the reported contracts. We were able to obtain the source code for 65 of the 125 reported contracts. Our manual inspection identified that all of the contracts are true positives. They either contained a faulty arithmetic check or no arithmetic check at all.

**Unhandled Exception.** Since none of the previous works analyzed unhandled exceptions, we manually analyzed the source code of the contracts reported by HORUS. However, we limited our validation to a random sample of 100 contracts since manually analyzing 1,068 contracts is infeasible. We find that all of the 100 contracts contained in their source code either a direct call or a function call that did not check the return value. Therefore, we conclude that HORUS reports no false positives on the detection of unhandled exceptions.

**Short Address.** We compared our results to those reported by SODA. SODA detected 726 contracts and 6,599 transactions, whereas HORUS detected 55 contracts and 275 transactions. After further investigation, we found that the contracts and transactions detected by HORUS were also detected by SODA. We also found that SODA reported transactions that failed or where the transferred amount was zero, while HORUS only reported transactions that were successful and where an ERC-20 transfer event was successfully triggered with an amount larger than zero. Moreover, we were able to obtain the source code for 5 of the

reported contracts and confirm that the `transfer` or `transferFrom` functions contained inside those contracts do not validate the input length of parameters.

## 5 Analysis

In this section, we demonstrate the practicality of HORUS in detecting and analyzing real-world smart contract attacks via an analysis of our evaluated results and a case study on the recent Uniswap and Lendf.me incidents.

### 5.1 Volume and Frequency of Attacks

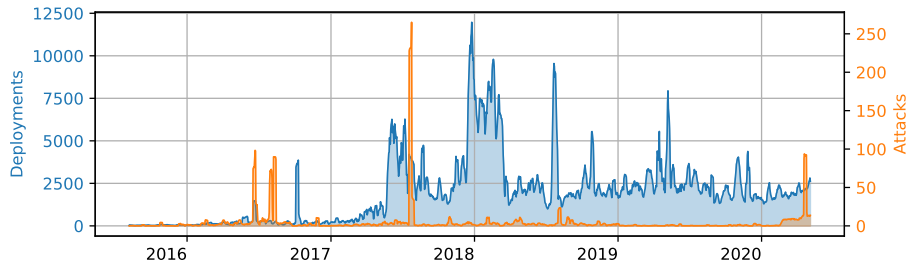


Fig. 3: Weekly average of daily contract deployments and attacks over time.

Fig. 3 depicts the weekly average of daily attacks in comparison to the weekly average of daily deployments. We state that the peak of weekly deployed contracts was at the end of 2017, and that the largest volume of weekly attacks occurred before this peak. Moreover, most attacks seem to occur in clusters of the same day. We suspect that attackers scan the blockchain for similar vulnerable contracts and exploit them at the same time. The first three spikes in the attacks correspond to the DAO and Parity wallet hacks, whereas the last spike corresponds to the recent Uniswap/Lendf.me hacks.

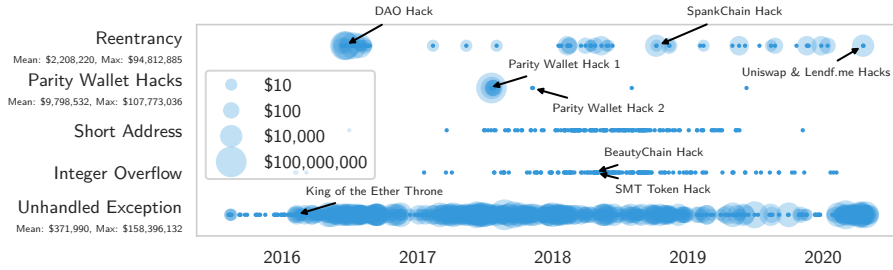


Fig. 4: Volume and frequency of smart contract attacks over time.

Fig. 4 depicts the occurrences of adversarial transactions per vulnerability type that we measured during our evaluation. While reentrancy attacks seem

to occur more sporadically, other types of vulnerabilities such as unhandled exceptions are triggered rather continuously. Overall, we see that over time less contracts became victims to short address attacks and integer overflows, suggesting that smart contracts have become more secure over the past few years. However, we also see that smart contracts still remain vulnerable to well-known vulnerabilities such as reentrancy and unhandled exceptions, despite automated security tools being available. Fig. 4 also illustrates for each adversarial transaction the amount of USD that was either stolen (reentrancy and Parity wallet hack 1) or locked (unhandled exception and Parity wallet hack 2). The USD amounts were calculated by multiplying the price of one ether at the time of the attack times the ether extracted via our Datalog query. We do not provide USD amounts for short address attacks and integer overflows, because these attacks involve stolen ERC-20 tokens and we were not able to obtain the historical prices of these tokens. We can see that the DAO hack and the first Parity wallet hack remain the two most devastating attacks in terms of ether stolen, with ether worth 94,812,885 USD and 107,773,036 USD, respectively. We marked well-known incidents such as the DAO hack, or the two Parity wallet hacks for the reader’s convenience and to demonstrate that HORUS is able to detect them.

## 5.2 Forensic Analysis on Uniswap and Lendf.me Incidents

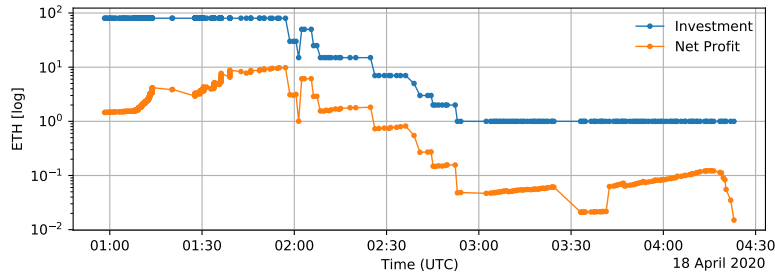


Fig. 5: Invested ETH and net profit made by Uniswap attackers over time.

**Uniswap.** On April 18, 2020, attackers were able to drain a large amount of ether from Uniswap’s liquidity pool of ETH-imBTC [11]. They purposely chose the imBTC token as it implements the ERC777 standard, which would allow them to register a callback function and therefore perform a reentrancy attack on Uniswap. The attackers would start by purchasing imBTC tokens for ETH. Afterward, they would exchange half of the purchased imBTC tokens within the same transaction back to ETH. However, the latter would trigger a callback function that the attackers registered before the attack, allowing them to take control and call back the Uniswap contract to exchange the remaining half of imBTC tokens to ETH before the conversion rate was updated. Thus, the attackers could trade the second batch of imBTC tokens at a more profitable conversion rate. Interestingly, this vulnerability was known to Uniswap and was

publicly disclosed precisely a year before the attack [5].

We used HORUS to extract and analyze all the transactions mined on that day, and identified a total of 525 transactions performing reentrancy attacks against Uniswap with an accumulated profit of 1,278 ETH (232,239.46 USD). The attack began at 00:58:19 UTC and ended roughly 3.5 hours later at 04:22:58 UTC. Fig. 5 depicts a timeline of the attack, showing the amount of ether that the attackers invested and the net profit they made per transaction. We see that the net profit goes down over time. The highest profit made for a single transaction was roughly 9.79 ETH (1,778.72 USD), while the lowest profit was 0.01 ETH (2.73 USD). The attackers began their attack by purchasing tokens for roughly 80 ETH and went over time down to 1 ETH. Moreover, we see that the profit was mostly tied to the amount of ether that the attackers were investing (i.e., using to purchase imBTC tokens). However, we also see that sometimes there were some fluctuations, where the attackers were making more profit while they would invest the same amount of ether. This is probably due to other participants trading imBTC on Uniswap during the attack and therefore influencing the exchange rates. In the last step, we traced the entire ether flow from the attackers account for up to 5 hops using HORUS’s tracing capabilities. Our transaction graph analysis reveals that the attackers exchanged roughly 702 ETH (55% of the stolen funds) for tokens on different exchanges: 589 ETH on Uniswap for WETH, DAI, USDC, BAT, and MKR, 31 ETH on Compound, and 82 ETH on 1inch.exchange. The latter is of particular interest for law enforcement agencies as 1inch.exchange keeps track of IP addresses of transactions performed over their platform [37], which can be useful in deanonymizing the attackers.

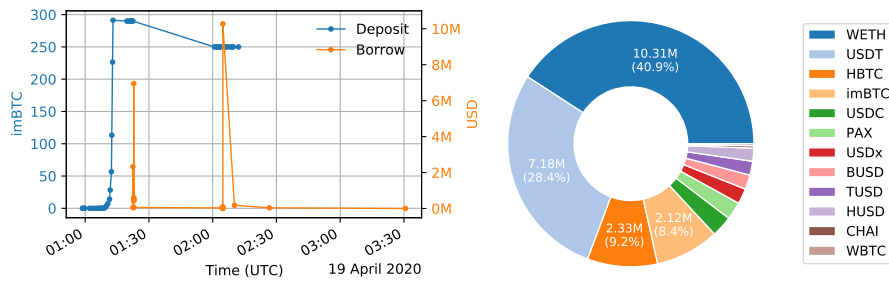


Fig. 6: Deposited and borrowed tokens by Lendf.me attackers over time.

**Lendf.me.** On April 19, 2020, attackers were able to drain all of Lendf.me’s liquidity pools [10]. Similar to the Uniswap hack, the attackers exploited the fact that Lendf.me was trading imBTC and could register a callback function to perform a reentrancy attack. The attackers would start by depositing  $x$  amount of imBTC tokens into Lendf.me’s liquidity pool. Next, still within the same transaction, they would deposit another amount  $y$ , however, this time triggering the callback function registered by the attackers, which would withdraw the previously deposited  $x$  tokens from Lendf.me. By the end of the transaction,

the imBTC balance of the attackers on the imBTC token contract would be  $x - y$ , but the imBTC balance on the Lendf.me contract would be  $x + y$ , thereby increasing their imBTC balance on Lendf.me by  $x$  without actually depositing it. Similar to Uniswap, the issue here is that the user’s balance is only updated after the transfer of tokens, thus the update is based on data before the transfer and therefore ignoring any updates made in between.

Using HORUS, we extracted and analyzed all the transactions mined on that day. We identified a total of 46 transactions performing reentrancy attacks against Lendf.me, and 19 transactions using the stolen imBTC tokens to borrow other tokens. Fig. 6 shows on the left the amount of imBTC tokens that the attackers deposited during the attack and the amount of USD that the attackers made by borrowing other tokens. The right-hand side of Fig. 6 depicts the number of tokens in USD that the attackers borrowed from Lendf.me. The attackers borrowed from 12 different tokens, worth together 25,244,120.74 USD, where 10.31M USD are only from borrowing WETH. The attackers launched their attack at 00:58:43 UTC and stopped 2 hours later at 02:12:11 UTC. They started depositing low amounts of imBTC and increased their amounts over time up to 291.35 imBTC. The borrowing started at 01:22:27 UTC and ended at 03:30:42 UTC. Finally, we used HORUS to trace the flow of tokens from the attackers account for up to 3 hops. We found that the attackers initially traded some parts of the stolen tokens for other tokens on ParaSwap, Compound, Aave, and 1inch.exchange. However, at 14:16:52 UTC, thus about 10 hours later, the attackers started sending all the stolen tokens back to Lendf.me’s admin account (0xa6a6783828ab3e4a9db54302bc01c4ca73f17efb). Lendf.me then moved all the tokens into a recovery account (0xc88fcc12f400a0a2cebe87110dcde0dafd29f148) where users could then reclaim their tokens.

## 6 Related Work

**Static Analysis.** Researchers proposed a number of tools to detect smart contract vulnerabilities via static analysis. Luu et al. [26] proposed OYENTE, the first symbolic execution tool for smart contracts. Other tools such as OSIRIS [15], combine symbolic execution and taint analysis to detect integer bugs. MYTHRIL [29] uses a mix of symbolic execution and control-flow checking. MAIAN [31] employs inter-procedural symbolic execution. TEETHER [25] automatically generates exploits for smart contracts. HONEYBADGER [17] performs symbolic execution to detect honeypots. However, symbolic execution is often unable to explore all program states, making it generally unsound. Formal verification tools were proposed [27, 45], together with a formal definition of the EVM [20]. ETHBMC [18] uses bounded model checking to detect vulnerabilities, whereas ETHOR [38] uses reachability analysis. ZEUS [23] verifies the correctness of smart contracts using abstract interpretation and model checking. SMARTCHECK [43] checks Solidity source code against XPath patterns. VERISMART [39] leverages counter example-based inductive synthesis to detect arithmetic bugs. SECURIFY [44] extracts semantic information from the dependency graph to check



for compliance and violation patterns using Datalog. VANDAL [2] converts EVM bytecode to semantic logic relations and checks them against Datalog queries. The main difference between these works and ours, is that they analyze the bytecode of smart contracts, whereas we analyze the execution of transactions.

**Dynamic Analysis.** Although less apparent, a number of dynamic approaches have also been proposed. ECFCHECKER [19] enables the runtime detection of reentrancy attacks via a modified EVM. SEREUM [36] proposes a modified EVM to protect deployed smart contracts against reentrancy attacks. ÆGIS [14, 16] presents a smart contract and a DSL to protect against all kinds of runtime attacks. SODA [3] uses a modified Ethereum client to inject custom modules for the online detection of malicious transactions. Perez et al. [34] use Datalog to study the transactions of vulnerable smart contracts that have been detected by previous works. ETHSCOPE [48] loads historical data into an Elasticsearch database and adds dynamic taint analysis to the client to analyze transactions. Zhou et al. [51] study attacks and defenses by encoding transactional information as action trees and result graphs. TXSPECTOR [49] is a concurrent work to ours and adopts the Datalog facts proposed by VANDAL. However, these facts were designed to analyze bytecode and do not allow to detect multi-transactional attacks. In contrast to these works, our work does not modify the Ethereum client. Instead, we dynamically inject our custom tracer into the client. We also provide a new set of Datalog facts that allow to check for multi-transactional attacks and describe data flows between instructions via dynamic taint analysis. Finally, none of the aforementioned tools provide means to trace stolen assets across the Ethereum blockchain.

## 7 Conclusion

A wealth of automated vulnerability detection tools for Ethereum smart contracts were proposed over the past years. This raises the question whether the security of smart contracts has improved. In this paper, we presented the design and implementation of an extensible framework for carrying out longitudinal studies on detecting, analyzing, and tracing of smart contract attacks. We analyzed transactions from August 2015 to May 2020 and identified 8,095 attacks as well as 1,888 vulnerable contracts. Our analysis revealed that while the number of attacks seems to have decreased for attacks such as integer overflows, unhandled exceptions and reentrancy attacks still seem to remain present despite an abundance of new smart contract security tools. Finally, we also presented an in-depth analysis on the recent Uniswap and Lendf.me incidents.

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## References

1. Atzei, N., Bartoletti, M., Cimoli, T.: A survey of attacks on ethereum smart contracts (sok). In: International Conference on Principles of Security and Trust. pp. 164–186. Springer (2017)
2. Brent, L., Jurisevic, A., Kong, M., Liu, E., Gauthier, F., Gramoli, V., Holz, R., Scholz, B.: Vandal: A scalable security analysis framework for smart contracts. arXiv preprint arXiv:1809.03981 (2018)
3. Chen, T., Cao, R., Li, T., Luo, X., Gu, G., Zhang, Y., Liao, Z., Zhu, H., Chen, G., He, Z., et al.: Soda: A generic online detection framework for smart contracts. In: Proceedings of the Network and Distributed System Security Symposium (NDSS’20) (2020)
4. CoinMarketCap: Top 100 Cryptocurrencies by Market Capitalization (September 2020), <https://coinmarketcap.com>
5. ConsenSys Diligence: Uniswap Audit (September 2019), <https://github.com/ConsenSys/Uniswap-audit-report-2018-12>
6. Etherscan: The DAO (2016), <https://etherscan.io/address/0xbb9bc244d798123fde783fcc1c72d3bb8c189413>
7. Etherscan: The Dark DAO (2016), <https://etherscan.io/address/0x304a554a310c7e546dfe434669c62820b7d83490>
8. Etherscan: DSEthToken (2017), <https://etherscan.io/address/0xd654bdd32fc99471455e86c2e7f7d7b6437e9179>
9. Etherscan: HODLWallet (2018), <https://etherscan.io/address/0x4a8d3a662e0fd6a8bd39ed0f91e4c1b729c81a38>
10. Etherscan: Lendf.Me - MoneyMarket (2019), <https://etherscan.io/address/0x0eee3e3828a45f7601d5f54bf49bb01d1a9df5ea>
11. Etherscan: Uniswap: imBTC (2019), <https://etherscan.io/address/0xffcf45b540e6c9f094ae656d2e34ad11cdfdb187>
12. Etherscan: Ethereum Daily Transactions Chart (September 2020), <https://etherscan.io/chart/tx>
13. Etherscan: Wrapped Ether (September 2020), <https://etherscan.io/address/0xc02aaa39b223fe8d0a0e5c4f27ead9083c756cc2>
14. Ferreira Torres, C., Baden, M., Norvill, R., Jonker, H.: ÆGIS: Smart Shielding of Smart Contracts. In: Proceedings of the 2019 ACM SIGSAC Conference on Computer and Communications Security. pp. 2589–2591 (2019)
15. Ferreira Torres, C., Schütte, J., State, R.: Osiris: Hunting for integer bugs in ethereum smart contracts. In: Proceedings of the 34th Annual Computer Security Applications Conference. pp. 664–676. ACSAC ’18, ACM, New York, NY, USA (2018). <https://doi.org/10.1145/3274694.3274737>
16. Ferreira Torres, C., Steichen, M., Norvill, R., Fiz Pontiveros, B., Jonker, H.: ÆGIS: Shielding Vulnerable Smart Contracts Against Attacks. In: Proceedings of the 15th ACM Asia Conference on Computer and Communications Security (ASIA CCS’20), October 5–9, 2020, Taipei, Taiwan (2020)
17. Ferreira Torres, C., Steichen, M., State, R.: The Art of The Scam: Demystifying Honey pots in Ethereum Smart Contracts. In: 28th USENIX Security Symposium (USENIX Security 19). pp. 1591–1607. USENIX Association, Santa Clara, CA (Aug 2019)
18. Frank, J., Aschermann, C., Holz, T.: ETHBMC: A bounded model checker for smart contracts. In: 29th USENIX Security Symposium (USENIX Security 20). USENIX Association, Boston, MA (Aug 2020)

19. Grossman, S., Abraham, I., Golan-Gueta, G., Michalevsky, Y., Rinetzky, N., Sagiv, M., Zohar, Y.: Online detection of effectively callback free objects with applications to smart contracts. *Proceedings of the ACM on Programming Languages* **2**(POPL), 48 (2017)
20. Hildenbrandt, E., Saxena, M., Rodrigues, N., Zhu, X., Daian, P., Guth, D., Moore, B., Park, D., Zhang, Y., Stefanescu, A., Rosu, G.: Kevm: A complete formal semantics of the ethereum virtual machine. In: 2018 IEEE 31st Computer Security Foundations Symposium (CSF). pp. 204–217 (2018)
21. Jiang, B., Liu, Y., Chan, W.: Contractfuzzer: Fuzzing smart contracts for vulnerability detection. In: *Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering*. pp. 259–269. ACM (2018)
22. Jordan, H., Scholz, B., Subotić, P.: Soufflé: On synthesis of program analyzers. In: *International Conference on Computer Aided Verification*. pp. 422–430. Springer (2016)
23. Kalra, S., Goel, S., Dhawan, M., Sharma, S.: Zeus: Analyzing safety of smart contracts. In: NDSS. pp. 1–12 (2018)
24. Klint Finley: A \$50 Million Hack Just Showed That the DAO Was All Too Human (June 2016), <https://www.wired.com/2016/06/50-million-hack-just-showed-dao-human/>
25. Krupp, J., Rossow, C.: tether: Gnawing at ethereum to automatically exploit smart contracts. In: 27th USENIX Security Symposium (USENIX Security 18). pp. 1317–1333 (2018)
26. Luu, L., Chu, D.H., Olickel, H., Saxena, P., Hobor, A.: Making Smart Contracts Smarter. In: *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security - CCS'16*. pp. 254–269. ACM Press, New York, New York, USA (2016). <https://doi.org/10.1145/2976749.2978309>
27. Mavridou, A., Laszka, A.: Tool demonstration: Fsolidm for designing secure ethereum smart contracts. In: *International Conference on Principles of Security and Trust*. pp. 270–277. Springer (2018)
28. Medvedev, Evgeny: Ethereum ETL v1.3.0 (April 2019), <https://github.com/blockchain-etl/ethereum-etl>
29. Mueller, B.: Smashing ethereum smart contracts for fun and real profit.(2018). In: *The 9th annual HITB Security Conference* (2018)
30. NCC Group: Decentralized Application Security Project (or DASP) Top 10 of 2018 (December 2018), <https://dasp.co>
31. Nikolić, I., Kolluri, A., Sergey, I., Saxena, P., Hobor, A.: Finding the greedy, prodigal, and suicidal contracts at scale. In: *Proceedings of the 34th Annual Computer Security Applications Conference*. pp. 653–663. ACM (2018)
32. PeckShield - batchOverflow Bug: ALERT: New batchOverflow Bug in Multiple ERC20 Smart Contracts (CVE-2018-10299) (April 2018), <https://blog.peckshield.com/2018/04/22/batchOverflow/>
33. PeckShield - proxyOverflow Bug : New proxyOverflow Bug in Multiple ERC20 Smart Contracts (CVE-2018-10376) (April 2018), <https://blog.peckshield.com/2018/04/25/proxyOverflow/>
34. Perez, D., Livshits, B.: Smart contract vulnerabilities: Vulnerable does not imply exploited. In: 30th USENIX Security Symposium (USENIX Security 21). USENIX Association, Vancouver, B.C. (Aug 2021)
35. Petrov, S.: Another parity wallet hack explained (nov 2017), <https://medium.com/@Pr0Ger/another-parity-wallet-hack-explained-847ca46a2e1c>

36. Rodler, M., Li, W., Karame, G., Davi, L.: Sereum: Protecting existing smart contracts against re-entrancy attacks. In: Proceedings of the Network and Distributed System Security Symposium (NDSS'19) (2019)
37. Ryan Sean Adams: (September 2020), <https://twitter.com/RyanSAdams/status/1252574107159408640>
38. Schneidewind, C., Grishchenko, I., Scherer, M., Maffei, M.: ethor: Practical and provably sound static analysis of ethereum smart contracts. arXiv preprint arXiv:2005.06227 (2020)
39. So, S., Lee, M., Park, J., Lee, H., Oh, H.: Verismart: A highly precise safety verifier for ethereum smart contracts. In: 2020 IEEE Symposium on Security and Privacy (SP). pp. 1678–1694. IEEE (2020)
40. StackExchange: Why is my node synchronization stuck/ extremely slow at block 2,306,843? (November 2016), <https://ethereum.stackexchange.com/questions/9883/why-is-my-node-synchronization-stuck-extremely-slow-at-block-2-306-843>
41. Szabo, N.: Formalizing and securing relationships on public networks. *First Monday* **2**(9) (1997)
42. Szilágyi, P.: Go-Ethereum Management APIs - JavaScript-based tracing (jan 2020), <https://github.com/ethereum/go-ethereum/wiki/Management-APIs#javascript-based-tracing>
43. Tikhomirov, S., Voskresenskaya, E., Ivanitskiy, I., Takhaviev, R., Marchenko, E., Alexandrov, Y.: Smartcheck: Static analysis of ethereum smart contracts. In: 2018 IEEE/ACM 1st International Workshop on Emerging Trends in Software Engineering for Blockchain (WETSEB). pp. 9–16. IEEE (2018)
44. Tsankov, P., Dan, A., Drachler-Cohen, D., Gervais, A., Buenzli, F., Vechev, M.: Securify: Practical security analysis of smart contracts. In: Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security. pp. 67–82. ACM (2018)
45. Wang, Y., Lahiri, S., Chen, S., Pan, R., Dillig, I., Born, C., Naseer, I.: Formal specification and verification of smart contracts for azure blockchain (April 2019), <https://www.microsoft.com/en-us/research/publication/formal-specification-and-verification-of-smart-contracts-for-azure-blockchain>
46. Wood, G.: Solidity 0.6.8 documentation (May 2020), <https://solidity.readthedocs.io/en/v0.6.8/>
47. Wood, G., et al.: Ethereum: A secure decentralised generalised transaction ledger. *Ethereum project yellow paper* **151**(2014), 1–32 (2014)
48. Wu, L., Wu, S., Zhou, Y., Li, R., Wang, Z., Luo, X., Wang, C., Ren, K.: Ethscope: A transaction-centric security analytics framework to detect malicious smart contracts on ethereum. arXiv preprint arXiv:2005.08278 (2020)
49. Zhang, M., Zhang, X., Zhang, Y., Lin, Z.: TXSPECTOR: Uncovering attacks in ethereum from transactions. In: 29th USENIX Security Symposium (USENIX Security 20). pp. 2775–2792. USENIX Association (Aug 2020)
50. Zhao, W.: \$30 Million: Ether Reported Stolen Due to Parity Wallet Breach (jul 2017), <https://www.coindesk.com/30-million-ether-reported-stolen-parity-wallet-breach>
51. Zhou, S., Yang, Z., Xiang, J., Cao, Y., Yang, Z., Zhang, Y.: An ever-evolving game: Evaluation of real-world attacks and defenses in ethereum ecosystem. In: 29th USENIX Security Symposium (USENIX Security 20). pp. 2793–2810. USENIX Association (Aug 2020)