TIME-TRAVEL INVESTIGATION: TOWARDS BUILDING A SCALABLE ATTACK DETECTION FRAMEWORK ON ETHEREUM

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ABSTRACT

As one of the representative blockchain platforms, Ethereum has attracted lots of attacks. Due to the existed financial loss, there is a pressing need to perform timely investigation and detect more attack instances. Though multiple systems have been proposed, they suffer from the scalability issue due to the following reasons. First, the tight coupling between malicious contract detection and blockchain data importing makes them infeasible to repeatedly detect different attacks. Second, the coarse-grained archive data makes them inefficient to replay transactions. Third, the separation between malicious contract detection and runtime state recovery consumes lots of storage.

In this paper, we present the design of a scalable attack detection framework on Ethereum. It overcomes the scalability issue by saving the Ethereum state into a database and providing an efficient way to locate suspicious transactions. The saved state is fine-grained to support the replay of arbitrary transactions. The state is well-designed to avoid saving unnecessary state to optimize the storage consumption. We implement a prototype named EthScope and solve three technical challenges, i.e., incomplete Ethereum state, scalability, and extensibility. The performance evaluation shows that our system can solve the scalability issue, i.e., efficiently performing a large-scale analysis on billions of transactions, and a speedup of around 2,300x when replaying transactions. It also has lower storage consumption compared with existing systems. The result with three different types of information as inputs shows that our system can help an analyst understand attack behaviors and further detect more attacks. To engage the community, we will release our system and the dataset of detected attacks.

1 Introduction

With an explosive growth of the blockchain technique, Ethereum [2] has become one of the representative platforms. One reason is due to its inborn support of smart contracts. Developers use smart contracts to build Decentralized Applications (DApps), ranging from gaming, lottery, Decentralized Finance (DeFi), and cryptocurrency, e.g., ERC20 tokens [6].

At the same time, attacks targeting Ethereum are increasing. By exploiting the vulnerabilities of smart contracts, attackers could make huge profits in a short time. For instance, in April 2016, attackers exploited the re-entrancy vulnerability in the DAO smart contract and stole around 3.6 million Ether [48]. Attackers used the similar vulnerability to attack the decentralized exchange Uniswap [30] (July 2019) and DeFi application Lend.Me [29] (April 2020). Besides, lots of other types of attacks have been observed in the wild [17, 18, 19].

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Figure 1: The typical flow of an investigation of attacks on Ethereum.

Accordingly, there is a pressing need for the security community to perform timely investigations on attacks and detect more attack instances that were not revealed. This requires the capability to quickly locate suspicious transactions based on various types of public information. For instance, suppose there is a reported attack to a smart contract (the victim contract) on the public forum, but the detail of such an attack is unknown. In order to understand the attack, an analyst needs to locate suspicious transactions that interact with the victim contract, and further construct the callgraph between the victim contract and others to understand their behaviors. After that, the analyst may need to detect more attack instances. In particular, he or she further locates candidate transactions² that are potentially related to the attack and *replay them*. By doing so, the analyst can monitor the runtime state of a smart contract and hook into its execution to detect more attacks. Fig. 1 shows this flow.

Note that, the investigation may continuously repeat the steps in Fig. 1. That's because the understanding of an attack needs multiple rounds of querying and analyzing transactions. This raises the challenge that *the analysis framework should be scalable to a large number of transactions* (until July 5th, 2020, Ethereum has 754, 614, 255 normal transactions and 962, 171, 044 internal transactions, respectively), i.e., *efficiently locating and replaying transactions*. ³

Limitations of existing systems Though multiple systems [28, 33, 38, 39, 47] have been proposed to detect malicious smart contracts ⁴, the scalability issue makes them ineffective to perform the time-travel investigation due to the following reasons.

- *Tight Coupling between malicious contract detection and blockchain data importing* (Limitation I) Some systems import the entire blockchain data from the genesis block and replay historical transactions. During this process, malicious contracts are detected based on pre-defined rules. The importing process is time-consuming (about ten days) and cannot be repeated. It is inflexible to repeatedly replay transactions, revise and debug detection rules, a considerable limitation to detect new attack instances.
- *Coarse-grained archive data* (Limitation II) To solve the previous limitation, systems could leverage the *archive mode* [21] of popular Ethereum clients to repeatedly replay arbitrary transactions, after importing the data once. However, the historical state is too coarse-grained to *efficiently* replay transactions, since unnecessary transactions are executed (Section 3.1). Our evaluation shows that it costs more than 47 minutes to replay 100 normal transactions. This is not scalable for real attack detection, which needs to replay tens of thousands and even millions of transactions (Section 5.1.3).
- Separation between malicious contract detection and runtime state recovery (Limitation III) Instead of using the coarse-grained archive data, recent systems recover and store the runtime information (called logical relation in the paper [28]) into a database. The further detection is based on the stored logical relation. This avoids the cost of repeatedly replaying transactions. However, the storage for the logical relation is huge. For instance, the logical relation database for blocks ranging from 7,000,000 to 7,200,000 consumes 2,949 GB [28]. Given the fact that Ethereum has around 10,400,000 blocks (as on July 5th, 2020) and this number is still increasing, it's not practical to detect attacks in the whole Ethereum blocks.

Our approach Our system takes the following approaches to overcome the limitations.

 $^{^{2}}$ To avoid the confusion with suspicious transactions used in step I, we call transactions that are potentially related to the attack in this step as candidate transactions.

³Because the investigation involves the replay of transactions to monitor the Ethereum state, it is like a time travel to certain points in time, hence the name *time-travel investigation*.

⁴In this paper, we interchangeably use the following two terms, i.e., malicious smart contracts and attacks, because attacks are usually automatically performed by malicious smart contracts.

- Limitation I: Our system does not perform the detection during the blockchain importing process. Instead, we save the Ethereum state, e.g., internal transactions, created smart contract code, into a database. Further detection is based on the saved state to locate suspicious transactions. This decouples the detection and the importing process.
- Limitation II: Our system replays arbitrary transactions in a scalable way. This is due to the well-designed and fine-grained state that has been retrieved in the previous step. By doing so, there is no need to reply unnecessary transactions in our system. For instance, our system only needs around one second to replay the same 100 normal transactions that consumed 47 minutes in the archive mode (Table 5).
- Limitation III: Our detection is performed at the same time when replaying transactions. It provides an extensive way for an analyst to specify detection rules, which are executed when replaying transactions. Thanks to the efficient replay engine, our system does not need to save unnecessary runtime information. For instance, our system only consumes 1,844 GB storage for the historical state in the 10.5 *million blocks* (as on July 22th, 2020), compared with 2,949 GB needed for 0.2 *million blocks* in TXSPECTOR [28]. This makes the detection among all Ethereum blocks possible.

System Implementation With the scalability requirement in mind, we have implemented an analysis framework named EthScope with three components.

Specifically, the first component, i.e., data aggregator, collects and recovers the critical blockchain state, including internal transactions, self-destructed smart contracts, the account balance of each block, and etc. The database is used to quickly locate suspicious transactions, and more importantly, provide fine-grained state that is needed by the replay engine.

The second component, i.e., replay engine, is able to *efficiently and repeatedly replay arbitrary and a large number of transactions*. This is critical to solve the scalability issue in existing systems. The saved blockchain state is carefully designed to replay transactions without executing unnecessary ones.

The third component, i.e., instrumentation framework, exposes interfaces for an analyst to dynamically instrument smart contracts and introspect the execution of transactions. An analyst can develop analysis scripts (using the JavaScript language) to analyze transactions and detect malicious smart contracts. Our framework reduces the performance overhead by a fine-grained design of instrumentation points and minimizes context switches between the EVM and the analysis script. Compared with JSTracer [15], our framework is more flexible and efficient (Table 5).

Evaluation We evaluate our system from two perspectives. We first evaluate the efficiency of our system. The performance evaluation shows that our system solves the scalability problem. Specifically, our system consumes 1, 817 GB for the state of 10, 400, 000 blocks. It is more efficient (around 2, 300x speedup) than existing ones when replaying transactions. Then we use three different types of public information to detect attacks on Ethereum. Specifically, we leverage a victim smart contract, a reported suspicious transaction, and the abnormal blockchain state as inputs to understand the attack and further detect more attack instances. The comparison with our system and other ones on the detection of the re-entrancy attack shows the accuracy of our system.

In summary, this paper makes the following main contributions:

- We present the flow of an investigation of attacks on Ethereum and summarize the limitations of existing systems and their reasons.
- We propose multiple methods to solve the scalability issue and present the design of a scalable framework to detect *real* attacks on Ethereum (Section 3).
- We implement a prototype and illustrate methods to address three technical challenges (Section 4).
- We evaluate the performance and effectiveness of our system with comprehensive experiments (Section 5).

To engage the community, we will release the source code of EthScope. We have released a trial system with a Docker image on https://hub.docker.com/r/swaywu/ethscope-trial.

2 Background

2.1 Ethereum Accounts

Each account in Ethereum has an address and associated balance in Ether. There exist two types of accounts, i.e., externally owned account (EOA) and smart contract account, respectively. EOAs are controlled by private keys, while



Figure 2: Normal and internal transactions. N: normal transactions; I: internal transactions.

smart contract accounts are controlled by their contract code [3]. Note that, both accounts can have Ether and other tokens, thus are associated with balances 5.

The address of a new smart contract is calculated from the number of transactions being sent (nonce) and the address of its creator, which is the account that creates the smart contract. Due to this, the newly created contract address is predictable by its creator. We will illustrate an attack that exploits this property in Section 5.2.

2.2 Transactions

A transaction is a type of message call that serves three purposes, including transferring Ether, deploying a smart contract, and invoking functions of a smart contract. Transactions on the Ethereum are normally initiated from EOAs, hence the name *normal transactions*.

Besides, there exists another type of transactions that are initiated from a smart contract. They are called *internal transactions*, which are used to invoke functions inside another smart contract, or transfer Ether to other accounts. For instance, the opcode CALL can be used to invoke a function of another smart contract, thus creating an internal transaction.

Note that, an internal transaction is always initiated from a normal transaction, since the smart contract that creates an internal transaction should be executed in the first place (from an EOA using a normal transaction.) Moreover, a normal transaction could create numerous internal transactions, if the invoked smart contract does so (invoking functions of other smart contracts.) Fig. 2 shows an overview of normal and internal transactions.

2.3 Ethereum State

Ethereum's nodes are devices participating in validating transactions. There are four types of state in Ethereum, which are useful to analyze and replay transactions. They include block information, normal transaction information, internal transaction information and accounts, as shown in the following.

- 1. Block information. The block information includes block number, block hash, and etc.
- 2. *Normal transaction information.* The normal transaction information includes addresses of the sender and the receiver, transaction hash, transaction data, transaction values, and etc.
- 3. *Internal transaction information*. The internal transaction information is basically the same as the normal transaction, plus the depth of the call stack of EVM.
- 4. *Account state*. The account state includes balance, nonce, code and storage of each account (including EOAs and smart contract accounts).

Normally, a full Ethereum node only permanently stores the block information, normal transaction information and the account state of the *latest blocks*. When synchronizing from the network, users can specify an option, e.g, -gcmode=archive in Geth, to retain a snapshot of accounts' state for each block. With the time-serial accounts' state, users can use the API debug.trace_transaction to replay arbitrary transactions in the exact manner as it was executed on the network. However, this method is not scalable. We will discuss the way used in our system to improve the performance of the replay process in Section 3.1.

2.4 Smart Contracts

Ethereum virtual machine A smart contract is a program that runs on an underlying Ethereum virtual machine (EVM) to transit the global state of the Ethereum network. A smart contract is usually programmed using a high-level language, e.g., Solidity, and then is compiled into low-level machine instructions (called *opcodes*), which will be fetched, decoded and executed by EVM.

⁵A smart contract account can have balances may contradict one's intuition.

Table 1: The comparison of state that could be retrieved by existing systems. Block: block information; NT: Normal transaction information; IT: internal transaction information; Account: Account state (Section 2.3). \checkmark : support; \times : not support; \triangle : partial support.

	Block	NT	IT	Account	Interface
Ethereum full node	\checkmark	\checkmark	×	×	×
Archive node [21]	\checkmark	\checkmark	×	\triangle^{a}	×
Etherscan [25]	\checkmark	\checkmark	\triangle^{b}	\triangle^{c}	\triangle^{d}
BigQuery [31]	\checkmark	\checkmark	\checkmark	×	\checkmark
Our system	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark

 \triangle^{a} : The account state is coarse-grained that unnecessary transactions will be replayed (Section 5.1.3). \triangle^{b} : Etherscan does not provide the invocation data of internal transactions.

 \triangle^{c} : The account state provided by Etherscan does not support the replay of transactions.

 \triangle^d : Etherscan does not support customized query for a large number of transactions, such as SQL.

EVM is a stack-based virtual machine. It has a virtual stack with 1,024 elements. All computations are performed on the stack. It means the operands, the result of intermediate operations are stored on the stack. For instance, when executing the ADD opcode to add two operands, EVM will pop two values from the stack, add them together and then push the result on the stack.

Besides the stack, there are four other types of data locations in EVM, memory, storage, input field, and ret field. The memory, input data and ret field are used to store temporary data such as function arguments, local variables, and return values. They are volatile, which means their values will be lost when the execution of a smart contract is finished. In contrast, the storage is a (per-account) persistent key-value store. For instance, a gaming smart contract could leverage the storage to maintain the balance of each player.

Function invocation As discussed in Section 2.2, internal transactions are used to invoke smart contract functions. This is achieved through executing a message call [22] launched by six opcodes, including CALL, CALLCODE, DELEGATECALL, STATICCALL, CREATE and CREATE2.

In a smart contract, there is a signature (four bytes) to denote the destination function that will be invoked. The signature is defined as the first four bytes of the hash value (SHA3) of the canonical representation of the function, including the function name and the parenthesized list of parameter types. Since this is a one-way function, it is hard to retrieve the function name from the signature. However, there is an online service [20] that we can lookup the function name given a signature.

Smart contract creation and destruction A smart contract could be created using two opcodes, i.e., CREATE and CREATE2. Both opcodes behave similarly, except the way to calculate the address of the newly created smart contract [14].

A smart contract can be self-destructed through the opcode SELFDESTRUCT. This opcode destroys the smart contract itself, and transfers all the Ether inside the contract to the address specified in the parameters of this opcode (the target address). However, if the account with the target address does not exist, this opcode will create a new account with this address. This means that the SELFDESTRUCT opcode implicitly creates a new account. Moreover, self-destruction a smart contract reclaims the gas since it frees the resources on the blockchain.

3 **System Design**

In the following, we will first illustrate technical challenges and then present the overall design of EthScope.

3.1 Technical Challenges

There are three technical challenges for building a scalable attack detection framework on Ethereum.

Incomplete blockchain state First, our system needs to provide a flexible interface to query the Ethereum state. For instance, when being used to understand and detect an attack, our system shall have the capability to quickly locate suspicious transactions from different perspectives, e.g., the values in the transactions or the number of internal transactions that exceed a certain threshold. Although there exist many methods that could be leveraged to explore Ethereum state, few of them fulfill our requirements. The details are shown in TABLE 1. Among them, Ethereum in BigQuery [31] maintains the Ethereum state into seven tables and provides an SQL interface to query the state. However, it lacks the account state that is critical for replaying transactions.



Figure 3: The overall architecture of EthScope.

Scalability Our system needs to replay and analyze a large number of transactions. There exist three different methods that are adopted by existing systems [33, 38, 39]. All of them suffer from the scalability issue.

The first one is to import the whole blockchain data with a customized EVM, which will execute all transactions (normal and internal ones) from the genesis block (the first block on the chain). During this process, attack-specific rules are executed. Representative tools include ECFChecker [39], ÆGIS [38] and SODA [33]. This method cannot selectively replay interested transactions. Thus, many unrelated ones have been executed, consuming lots of time. Moreover, the coupling between the detection and the importing process makes the detection of new attack instances hard, since the time-consuming importing process cannot be executed repeatedly.

The second way is to use the debug.trace_transaction API [13] exposed by Geth [4] to *replay* a transaction with the Ethereum archive node [47]. Though this method is more efficient than the previous one, it still suffers from the scalability issue. That's because the granularity of historical state maintained by the Ethereum archive node is a block rather than a transaction. In order to replay a transaction, all the (unnecessary) transactions before it inside the same block will be executed. Our system solves this challenge by recovering a transaction-level historical state.

The third one is first replaying all transactions and recording all the runtime information [28]. The following detection is on the recorded information. However, this method consumes lots of storage. According to the data reported in the paper [28], performing the attack detection in 2 millions blocks cost at least 2,949 GB. It's not scalable to analyze all the Ethereum blocks (more than 10 millions blocks).

Extensibility to detect different attacks Our system should be extensible to detect various attacks with analystprovided scripts. Geth has a mechanism called JSTracer [15] to introspect the execution of a smart contract. It allows users to specify a JavaScript file that will be invoked for every opcode executed. However, frequent switches between the EVM and the JavaScript file make it impractical to analyze a large number of transactions. Our system addresses this challenge with two optimizations. First, it has well-defined instrumentation points to minimize the number of context switches. The analysis script will be invoked on-demand (instead of each opcode) when defined instrumentation points are hit. Second, our framework is equipped with a dynamic taint analysis engine *inside the EVM*. Analysts do not need to implement their own taint engine usings JavaScript files, which further reduces the number of context switches.

3.2 Overall Design

We address these challenges with three components, i.e., data aggregator, replay engine, and instrumentation framework. The overall system architecture is shown in Fig. 3.

Specifically, data aggregator imports the whole blockchain data and collects the Ethereum state. The Ethereum state is collected by modifying the EVM. The collected state is stored in a cluster database equipped with a flexible query interface. An analyst could perform customized queries to locate transactions that are needed for further analysis. Note that, the process to import the blockchain data is a one-time effort. All the saved state could be queried without the need to import the blockchain data again. Our system also takes a careful design of the stored state to save the storage consuming. In fact, it consumes less storage than the Ethereum archive mode (Section 5.1.1).

The second component, i.e, replay engine, is used to replay arbitrary transactions. An analyst first locates candidate transactions and then feeds them to the engine. The replay engine obtains the related state including related accounts'

state for each transaction from the data aggregator. After that, it re-executes the transactions. Thanks for the transaction-level Ethereum state recovered by the data aggregator, our system does not need replay unnecessary transactions (Section 5.1.3).

The third component, i.e, instrumentation framework, provides a mechanism to customize the analysis. Specifically, an analyst can develop analysis scripts by defining callback functions for instrumentation points. For instance, a specific callback function could be defined and will be invoked if and only if the CALL opcode is executed. By doing so, our system avoids unnecessary context switches between EVM and the analysis script. During this process, the EVM state, including related stack and memory values, is provided to the script. Moreover, to facilitate the analysis, a dynamic taint engine is provided with well-defined APIs.

4 Implementation Details

We have implemented a prototype named EthScope. The data aggregator is implemented with around 1,137 lines changes to the Geth client. Our system uses the distributed search and analytics engine Elasticsearch [7] to store the Ethereum state and provide an interface to query them. The replay engine and instrumentation framework are implemented with 5,191 lines changes to EVM. In the following, we will elaborate the implementation of each component.

4.1 Data Aggregator

State collection The collection of block information and normal transaction information is straightforward. Our system changes the EVM to collect the data before the execution of each block (block information) and after the execution of each normal transaction (normal transaction information).

Collecting internal transaction information and accounts' state requires our system to hook into the process of executing smart contracts. For instance, when the opcode SSTORE is executed, the method setState in EVM is triggered. We change this method and add the code to capture the state. Note that, the state is not immediately stored into the underlying database. Instead, we create a buffer and save the state into the database when the buffer is full.

One challenge is how to ensure the completeness and correctness of the collected state. In our system, we solve this challenge by comparing the collected state with ground truths. Specifically, for block information and normal transaction information, we can easily compare them with the data stored inside the Ethereum full node. For internal transaction information, we compare our data with the data provided by online services, e.g., Etherscan [25]. However, there are no ground truths for the transaction-grained historical accounts' state. We solve it in the replay engine (State verification in Section 4.2).

Data organization and query interface Our system takes the following methods to avoid the scalability issue caused by storage-consuming, while providing enough information to replay a transaction. Global variables of smart contracts consume lots of storage. That's because they are updated frequently in different blocks.

Theoretically, we need to store all the global variables for each transaction in each block. However, when replaying a transaction, only the variables touched by that transaction are needed. Thus, for each transaction, we only store the used global variables (storage values in Ethereum) in the database.

Table 7 in Appendix shows the detailed data schema. Specifically, the Code index 6 stores the smart contracts' code and the State index records the information about creating and destructing accounts. Remaining ones are stored in the Block index.

Thanks to the Elasticsearch, an analyst could leverage the Query DSL based on JSON to define queries [8] for customized analysis.

4.2 Replay Engine

In order to monitor the transaction behaviors at the runtime, we build an engine that is capable of replaying arbitrary transactions on Ethereum. Our engine is based on EVM of Geth, with modifications to add support to retrieve the state from data aggregator. Moreover, it provides interfaces to communicate with instrumentation framework (Section 4.3).

⁶The index in Elasticsearch is similar to the database in a relational database.

Table 2: Three types of instrumentation points supported in our system. O: opcode-orientated; T: transaction-orientated; C: context-orientated.

Instrumentation Points	Туре	Description
{op}	0	before and after the opcode {op}
after{Op}	0	is executed
transactionStart	т	before and after an external
transactionEnd	1	transaction is executed
contractStart	C	before and after a new contract
contractEnd	C	is executed

Group transactions The input to replay engine is a list of hash values for the transactions to be analyzed. In order to speed up the process of obtaining related data from data aggregator, our system divides transactions into different groups, with a threshold that each group contains no more than 10,000 transactions. This threshold is related to the size of the system memory. For each group, replay engine first retrieves the historical state in a batch, and then replays transactions in the group.

Retrieve Ethereum historical state In order to replay a normal transaction, we need to retrieve the Ethereum historical state from data aggregator. First, we get the block and transaction information such as Difficulty and GasLimit from the Block index. Second, we retrieve the code of smart contracts that are related to this normal transaction in the nested field GetCodeList inside the field Transactions. That's because a normal transaction could involve *multiple smart contracts*. We retrieve the code for all the smart contracts. Third, we obtain all accounts' state: nonce, balance and storage values that the transaction will load. When the normal transaction is to create a new smart contract, we need to retrieve the deploying code of the new smart contract from the index Code, which is the input of this normal transaction, too. Table 7 in Appendix shows the details of the mentioned fields and indices.

Execute transactions After retrieving the historical state, replay engine executes the transactions. During this process, callback functions defined in the analysis script will be invoked. In order to speed up the process, our system further divides transactions in a group into different clusters according to the number of CPU cores, and executes transactions inside different clusters in parallel.

Verify state After replaying each normal transaction, replay engine will compare the used gas and output of this transaction with the same fields in the normal transaction information in data aggregator. This ensures the correctness of the replay process. Note that, the normal transaction information in data aggregator has been verified (State collection in Section 4.1).

4.3 Instrumentation Framework

The instrumentation framework aims to provide extensible APIs for an analyst to develop analysis scripts to detect new attack instances. Besides, instrumentation framework provides a dynamic taint engine to facilitate the analysis of control dependency and data dependency.

Overview The framework is hooked into the replay engine and provides JavaScript interfaces. Our system uses the Duktape JavaScript engine binding for Go [10] to execute JavaScript functions inside the EVM developed in Go. Specifically, it defines *instrumentation points*, where the replay process will be suspended and user-specific callback functions (in JavaScript) will be invoked. At the same time, it provides the interfaces for analysis scripts to access the current execution context, such as stack values and memory values. When the callback function finishes its execution, the replay engine continues the smart contract's execution from the instruction after the instrumentation point.

Instrumentation points Our system supports three types of instrumentation points, i.e., *opcode-*, *transaction-* and *contract-oriented* ones. Table 2 shows an overview of these instrumentation points.

First, the *opcode-oriented* instrumentation links with two callback functions for each opcode, {op} and after {op}. They are launched before and after executing the opcode {op}.

Second, the *transaction-oriented* callbacks, including transactionStart and transactionEnd, are launched before and after the execution of a normal transaction. These two instrumentation points are usually used for the initialization and processing results in the analysis script. Note that, this type of instrumentation points only works for normal transactions, which are initialized from EOAs. For internal transactions that are initialized from smart contracts, they are covered in the *contract-oriented* instrumentation point.



Figure 4: The sequence of invoking callback functions at different types of instrumentation points. The code of the smart contract is for illustration only. O: *opcode-oriented*; T: *transaction-oriented*; C: *contract-oriented*.

Tuble 5. TH Is provided by our instrumentation framework.									
APIs to retrieve execution context									
op.getN()	stack.length()	memory.slice(start, end)	contract.getSelfAddress	0	getBalance(addr)	getBlo	ockNumber()	getPc()	
op.toNumber()	stack.peek(n)	memory.getUint(offset)	contract.getCodeAddres	ss()	getNonce(addr)	getTx	nIndex()	getGas()	
op.toString()			contract.getValue()		getCode(addr)	getTx	nHash()	getDepth()	
			contract.getInput()		getStorage(addr)			getReturnData()	
Other APIs									
	cfg.hijack(isJ	(ump)			params.get(l	(ey)			
		APIs to	assign, clear and chec	k tai	nt tags				
labelStack(n,tag) labelMemory(offset,size,tag) 1:			labelInput(o,s,t)	lab	elReturnData(o,s,	t)	labelStorag	e(addr,slot,tag)	
clearStack(n) clearMemory(offset,size)		clearInput(o,s)	clea	learReturnData(o,s) clearStora		clearStorag	e(addr,slot)		
peekStack(n) peekMemory(offset)		peekInput(o)	pee	peekReturnData(o) peekStora		peekStorag	e(addr,slot)		
peekMemorySlice(offset,size)		peekInputSlice(o,s)	pee	kReturnDataSlice	e(o,s)				

Table 3: APIs provided by our instrumentation framework.

Third, the *contract-oriented* callback functions, including contractStart and contractEnd, deal with function calls crossing smart contracts (internal transactions). These two functions are invoked at the start and at the end of the execution of a smart contract function.

Fig. 4 shows the sequence of invoking callback functions at different instrumentation points. When an EOA issues a normal transaction, transactionStart will be invoked, and then contractStart is executed. That's because the normal transaction initializes the execution of smart contract A. Then the callback functions for each opcode are launched, until the CALL opcode. This opcode invokes the function inside the smart contract B and creates the internal transaction. Since the smart contract B is executed, contractStart will be invoked again. After that, callback functions for different opcodes will be invoked accordingly.

Note that, the execution context is switched from the EVM to the Duktape JavaScript engine, only when a callback function is defined and the instrumentation point is hit at runtime. This minimizes the number of context switches between EVM and Duktape. Compared with the JSTracer inside the Geth, our implementation is more efficient (Section 5.1.3).

APIs to retrieve the execution context Our system provides multiple APIs to get the information of current execution context. Table 3 shows an overview of these APIs. We elaborate some of them in the following.

- *Normal transactions.* Attributes of normal transactions are obtained by invoking getBlockNumber, getTxnIndex and getTxnHash. These attributes are used to distinguish different normal transactions.
- Internal transactions. Two APIs contract.getSelfAddress and contract.getCodeAddress are used to retrieve the context contract and code contract. The code contract is the address of the callee smart contract. However, the context contract can be the caller and the callee smart contract, depending on the opcode used to invoke the contract. This complies with the definition in Geth [5]. The API contract.getValue returns the amount of Ether that is transferred into the code contract.

Every time an internal transaction starts, the EVM stack depth will be increased by one. On the contrary, every time an internal transaction ends, it will be decreased by one. The API getDepth is provided to get current EVM stack depth. By using this information, we can detect the occurrence of a recursive function call.

• *Parameters and return values*. The API contract.getInput returns the input data (parameters) when invoking a function, while getReturnData obtains return values.

```
1
 2
         sload: function(log){
 3
             contextContract = toHex(log.contract.getSelfAddress())
 4
             key = log.stack.peek(0).toString(16)
 5
             tag = contract+"_"+key
 6
             log.taint.labelStack(0, tag)
7
    },
 8
9
         jumpi: function(log) {
10
             tags = log.taint.peekStack(1)
11
             for (tag in tags) {
12
                 contextContract = tag.substring(0, tag.indexOf("_"))
13
                 key = tag.substring(tag.indexOf("_"))
14
                 console.log("Storage", key, "in contract", contextContract, "influenced the control flow.")
   }
15
16
   }
17
     }
```

Figure 5: An example of how to use the dynamic taint engine to assign and check taint tags.

- *The program counter and remaining gas.* APIs getPc and getGas return the current program counter and remaining gas.
- Accounts. APIs getBalance, getCode, getStorage return the current states of an account at any time.

Dynamic taint engine Dynamic taint analysis has been widely used for security applications. Our framework implements a dynamic taint engine that facilitates the development of analysis scripts.

Our taint analysis engine supports the taint tag propagation crossing different smart contracts. When the EVM triggers an internal transaction, it will pass input values from the caller's memory to the callee's input field. When the invocation returns, the return value is put into the caller's ret field. We propagate the taint tags in opcodes CALLDATALOAD, CALLDATACOPY and RETURNDATACOPY that operate stack, memory, ret and input field. Table 3 summarizes APIs to assign, clear and check taint tags. APIs label* allow an analyst to assign taint tags. APIs peek* and clear* allow an analyst to check and clear tags.

Fig. 5 shows an example of how to use these APIs. Specifically, two callback functions <code>sload</code> and <code>jumpi</code> are invoked before executing opcodes SLOAD and JUMPI, respectively. Inside the callback function <code>sload</code>, it assigns the taint tag to the value on the top of the stack (index 0) using <code>log.taint.labelStack(0, tag)</code>. Then the taint engine will propagate the tag, even crossing different contracts. When the callback function <code>jumpi</code> is executed, the <code>log.taint.peekStack(1)</code> checks whether the second value on the stack (index 1) has the taint tag. If so, it changes the program counter. Thus, by checking the taint tag, an analyst can get the storage variables that can influence the control flow.

5 Evaluation

In this section, we will present the evaluation result of EthScope by answering the following research questions. If not otherwise specified, the evaluation is performed on the dataset that contains the Ethereum state from the genesis block (mined on July 30th, 2015) to the 10, 400, 000th one (mined on July 5th, 2020).

- R1 What's the performance of EthScope and whether EthScope solves the scalability issue?
- R2 Whether EthScope can help understand the behaviors of suspicious transactions and detect more attack instances?
- R3 Whether EthScope performs better than previous systems in terms of detected attacks?

To answer **R1**, we report the comparison result of the storage consumption and the time used to replay transactions. The result shows that EthScope consumes less storage and has a speedup of around 2300x when replying transactions. This demonstrates the capability of our system to perform the analysis on a large number of transactions.

To answer **R2**, we use three different types of public information as inputs, including *a victim smart contract*, *a reported suspicious transaction*, and the *abnormal blockchain state*. For each type of information, our system first understands attack behaviors, and then detect more attack instances. We report the result in Section 5.2, Section 5.3, and Section 9.1 (in Appendix), respectively.

To answer **R3**, we compare the detection result of the re-entrancy attack with previous systems. Our evaluation shows that our system is more accurate than previous ones. We report the result in Section 5.4.

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Table 4	I ne	comparison	or the	storage	lisage
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	Blocks	Storage
Geth Archive Node	0 - 7,635,000	2,320GB
Trace DB of TXSPECTOR	0 - 7, 200, 000	1,577GB
Logic Relation DB of TXSPECTOR	7,000,000 - 7,200,000	2,949GB
data aggregator	0 - 10.507.977	1.844GB

Table 5: The comparison of JSTracer and our system to replay 100 normal transactions.

Tools		Retrieve State	Execute Script	Other
ISTracer		39m 6s 997ms	0m 16s 984ms	8m 13s 467ms
Total		47m 37s 448ms		
Our system		0m 0s 446ms	0m 0s 217ms	0m 0s 544ms
Our system	Total		0m 1s 207ms	

5.1 Performance and Scalability

In this section, we demonstrate the scalability of our system via evaluating its performance from the following perspectives. First, the storage use is more efficient than previous systems, while at the same it can support the replay of arbitrary transactions. Second, the data aggregator can help locate suspicious and candidate transactions in an efficient way. Third, the replay engine can replay arbitrary transactions, with a 2,300x speedup. All experiments were performed on a machine with four CPUs (Intel(R) Xeon(R) Silver 4110 CPU @ 2.10GHz) and 128GB memory.

5.1.1 Storage Use

The data aggregator in our system stores the saved Ethereum state. We compare the storage use of our system with other ones that also store the Ethereum state. Specifically, ECFCHecker, Sereum, and SODA leverage the *archive node of Geth* to perform the analysis. TXSPECTOR replays historical transactions in Ethereum to record EVM bytecode-level traces into a *trace DB*, and stores the logic relations into a *logic relation DB* [28].

As shown in Table 4, the Geth archive node [21] of the first 7.635 million blocks uses 2, 320 GB⁷. The trace DB of TXSPECTOR and logic relation DB of TXSPECTOR consume 1, 577 GB, and 2, 949 GB for 7.2 million and 0.2 million blocks, respectively. Obviously, TXSPECTOR requires more space to support its analysis.

Our system costs only 1,844 GB after collecting the Ethereum state for 10.5 million blocks. That's because it only collects necessary state information to perform the security analysis and replay transactions. Note that, our system does not scarify the analysis capability to save storage. In particular, even though it consumes less storage, it can fully support the query to locate candidate transactions and replay them, as shown in the experiments to answer **R2**. This result shows EthScope does not suffer from the scalability issue due to the storage consumption.

5.1.2 Query Transactions

The data aggregator provides an interface to locate transactions by querying the saved Ethereum state, e.g, a normal transaction with more than 1,000 internal transactions whose Ether transferred are large than a certain amount. Our evaluation shows that most querying tasks can be finished in seconds, while complicated ones may last for a few minutes. For instance, the collection of candidate transactions for the re-entrancy attack (Section 5.3) and the bad randomness attack (Section 5.2) both take less than 5 minutes (retrieved 209, 227 and 10, 296, 519 candidates from 754, 614, 255 normal transactions) in our experiments.

5.1.3 Replay Transactions

In the following, we will compare the performance of our system with *JSTracer* (in the archive mode) supported by Geth [4]. To the best of our knowledge, this is the only comparable counterpart that can *repeatedly replay and instrument transactions*.

First, we randomly pick 100 normal transactions that have triggered internal transactions. Then, we develop a script that has an equivalent functionality with the example [12] (*4byte_tracer.js*) provided by Geth. Finally, we use the JSTracer and our system to *replay* 100 normal transactions. Note that, a normal transaction could trigger multiple internal transactions, thereby the total number of replayed transactions is 2, 519.

Table 5 shows the comparison result of the transaction replay time between JSTracer and our system. Specifically, JSTracer spends more than 47 minutes to replay the transactions, while our system takes only around one second to

⁷This data is obtained from the official Ethereum blog [23].

replay them. The result suggests that our system outperforms JSTracer with an around 2,300x speedup. We further explore the possible reasons.

- Granularity of the Ethereum historical state To retrieve the Ethereum historical state of the 100 normal transactions, JSTracer had to *replay* 3, 289 additional normal transactions. However, EthScope can directly query finegrained accounts' state information from the data aggregator.
- Number of context switches JSTracer needs to switch to the JavaScript environment for every opcode. Alternatively, our instrumentation framework only performs context-switch when instrumentation points are hit. That is why JSTracer performed 1, 305, 864 context switches, while EthScope only performed 2, 502 ones.

The result demonstrates that our system can replay a large number of transactions. In fact, for the 10, 296, 519 normal transactions used to detect the new instances of the bad randomness attack, our system took 12 hours 7 minutes to replay all of them, which is quite difficult (if not impossible) for other systems to complete such a task.

Answers to Q1: Our system consumes less storage than other systems, while at the same time the stored Ethereum state can support replaying arbitrary transactions. Besides, the replay engine in our system is more efficient when replaying transactions. The lower storage consumption and efficient replay engine make the detection of attacks in the whole Ethereum blocks possible.

5.2 Type-I Input: A Victim Contract

An analyst may receive incomplete information, e.g., a smart contract is being attacked. However, there is no detailed information about the vulnerability of the victim contract, nor the information on how the attack works. Our system can help an analyst understand the attack, and detect more attack instances. We use the Fomo3D [24] as an example to illustrate how EthScope helps analysts reveal attacks from a victim smart contract. The input to our system is the address ⁸ of the victim smart contract.

5.2.1 Understand the Attack

As shown in Fig. 1, an analyst leverages our system to understand the attack behaviors.

Locate suspicious transactions To locate suspicious transactions that may involve in the attack, our first step is to construct the *money flow graph* to locate suspicious accounts. That's because the Fomo3D is a gambling app. The money will flow into (successful) attackers (and other lucky players). Fig. 6 shows the money flow graph constructed using transactions retrieved from the data aggregator. Specifically, nodes in the graph represent accounts, and edges represent the direct and indirect transactions with the Fomo3D game. The size of each node denotes the number of Ether it receives.

We observe that several accounts have a much larger size than others. It means these accounts have received much more Ether from the game than others. Initial analysis shows that three of them belong to Fomo3D (number 0, 1, and 6). We then take further analysis for other accounts.

Understand suspicious transactions We analyze a normal transaction ⁹ that invokes the smart contract (index 2 in the money flow graph) ¹⁰ to receive Ether from Fomo3D. To this end, we construct the dynamic call graph in Fig. 7. The nodes in the graph represent accounts (both EOA and smart contracts), and the edges denote Ether transfer or function invocation.

The call sequence of this graph shows that, the contract (0x94c0d0) transfers 0.1 Ether to the contract (0x50ac2e) (index 4), which further creates a new smart contract (0x78414f) (index 6). This *new* contract buys the key (index 9) with 0.1 Ether and then receives 0.126 Ether (index 17) from the game. The received Ether is transferred back to the contract (0x94c0d0) with a SELFDESTRUCT operation (index 18). During this process, it obtains a profit of 0.026 Ether.

There also exist many similar transactions related to the contract (0x94c0d0). These transactions get a lot of rewards from the Fomo3D game. We suspect the contract (0x94c0d0) has a mechanism to predict whether it can win the bonus before playing the game. Otherwise, it can not win every time. After locating all the transactions and smart contracts created from this account by querying the data aggregator, we find that the contract (0x94c0d0) indeed can predict whether it can win. That's because the Fomo3D game uses the address of the player (controlled by the attacker) as one of the sources to generate the random number that determines the winner.

⁸0xa62142888aba8370742be823c1782d17a0389da1

⁹0xee95751e94c8427f94ddf34e15bb322f681a0d264e9d2d21c3fc0d687dff22c2

 $^{^{10}0}x94c0d029a7b64bf443e89c5006089364c0d60d61$



Figure 6: The money flow graph of the Fomo3D smart contract. For better illustration, we use 180, 244 transactions to generate this graph. The total number of transactions with Fomo3D is much larger.

Fig. 8 shows (a simplified version of) the attack flow. There is a controller contract, which creates a lot of proxy contracts (more than 1,000) in advance. Then during the attack, the controller attack loops through each proxy contract. It calculates the address of a newly created smart contract (but does not create it.) because the address is predictable (Section 2.1). Then it uses this address and the block information to predict whether it will get the bonus by executing the same logic with the Fomo3D game. If so, the proxy smart contract creates the attacking contract, which further buys the key to play the game and win the bonus. After that, the attacking contract self-destructs itself to transfer the earned bonus to the controller smart contract.

Because the attack exploits the vulnerable process of the smart contract to generate a random number, we name this attack as the *bad randomness attack*.

5.2.2 Detect more attack instances

After understanding the above attack, we then use our system to detect more bad randomness attacks. Specifically, we first use the data aggregator to filter out transactions that are not related to the attack. Then we use the replay engine to replay the remaining transactions and the instrumentation framework to confirm new attack instances at runtime.

Locate candidate transactions In order to avoid replaying unnecessary transactions (costing lots of time), we first use the data aggregator to remove transactions that are not related to the bad randomness attack.

We label normal transactions that fulfill the following requirements as candidate transactions. First, it has triggered more than one internal transaction. Second, the triggered internal transaction has transferred Ether to another smart contract. That's because in order to launch the attack, attackers have to use a contract to transfer Ether to play the game, thus creating an internal transaction. This rule is conservative. It may label some benign transactions as candidates. However, we want to include as many candidate transactions as possible in this step and leverage the replay engine to confirm whether they are real attacks. In total, our system locates 10, 296, 519 candidate transactions.

Confirm the bad randomness attack After locating the candidate transactions, we then use the replay engine to replay them and confirm attacks at runtime.



Figure 7: The dynamic call graph of a suspicious transaction. We draw three types of information for an internal transaction: 1. Serial number and the opcode to trigger an internal transaction; 2. Transferred Ether, null means no Ether transferred; 3. Invoked function (we search the name from the 4byte function signature database [20]), null means that the input data is empty; (Square: EOA, Circle: smart contract; Grey Box: attacker, White Box: victim.)



Figure 8: The flow of the bad randomness attack.

The key observation of this attack is that the malicious contract is using the same algorithm to generate the random number as the victim contract. We develop the detection script as follows.

- 1. First, we find all the variables that are generated from block information, e.g., coinbase, gaslimit and etc. This is implemented using our taint analysis engine by setting the block information as taint sources.
- 2. Second, for each variable v found in the previous step, we check whether it influences the control flow of the smart contract. That's because we only care about the variables that can determine the winner. If so, we log its execution context C.
- 3. If there exist two same execution contexts in different internal transactions that are triggered by a same normal transaction, then the normal transaction is a malicious one that launches the attack. That's because two smart contracts are executing the same algorithm that uses the same random number sources to generate a variable that can influence the control flow to determine the winner.

Detection result We replayed 10, 296, 519 candidate transactions with our analysis script. After that, 40, 449 normal transactions are labeled as malicious ones. During this process, 272 malicious smart contracts are detected. We then group them based on their creators, i.e., EOAs that create these contracts. In total, we get 79 groups. We manually checked the malicious smart contracts created in each group and found that 74 of them are true positives. In total, they have initialized 40, 358 normal transactions to attack 95 victim smart contracts, which includes various gambling games. Table-I in the link ¹¹ shows the detailed information of victim contracts and the false positives.

5.3 Type-II Input: A Reported Suspicious Transaction

Besides the victim contract, an analyst may receive the information that a malicious transaction is attacking a smart contract. Though there may exist partial information of the attack, the details of the attack are unknown.

¹¹https://github.com/Anonymouspaper146/SP2021fallsubmission



Figure 9: The dynamic call graph of a suspicious transaction that exploits the DAO smart contract. We use four lines to describe an internal transaction: 1. Serial number and the opcode to trigger an internal transaction; 2. Transferred Ether, null means no Ether transferred; 3. Invoked function (we search the name from the 4byte function signature database [20]), null means that the input data is empty; 4. EVM stack depth. (Square: EOA, Circle: smart contract; Grey Box: attacker, White Box: victim;)

5.3.1 Understand the Attack

Attackers leveraged the re-entrancy vulnerability to launch the attack towards the DAO smart contract and stole 3.6 million Ether [48]. In this following, we will elaborate on the process to understand the attack by leveraging a reported transaction ¹². Then we will leverage the gained knowledge to detect more re-entrancy attacks.

Understand suspicious transactions The input is a reported transaction, e.g., from a public forum. An analyst needs to understand how the attack works.

We construct a dynamic call graph in Fig.9. The serial numbers of transactions are in chronological order. The 0th transaction is a normal transaction, and others are internal transactions triggered by the normal transaction. For better illustration, we only use the first 20 internal transactions to draw the graph. The actual number of internal transactions is 185.

By analyzing this graph, we can find two distinct features of transactions that launch the attack. First, there exists a loop in the graph. This is reasonable since the call to the fallback function that further invokes the vulnerable contracts will create a loop in the call graph. For instance, internal transactions 2, 7, and 8 create a loop that starts from and ends at the malicious contract (0xc0ee9db). Second, there should exist a special smart contract called *reentry point*, which is the smart contract that will be invoked again before its previous invocation completes. For instance, the DAO contract (0xbb9bc2) is a *reentry point*, since the EVM stack depths of internal transactions (index 3 to 9) are all bigger than internal transaction 2. That means before an invocation to the DAO contract 0xbb9bc2 (internal transaction 2) returns, another invocation (internal transaction 9) to the same contract happens.

5.3.2 Detect more attack instances

After understanding the re-entrancy attack, we detect more attack instances.

Locate candidate transactions According to the gained knowledge of the attack in the previous step, we use the following two rules to locate candidate transactions. We label a normal transaction as a candidate when it satisfies the following two conditions.

 $^{^{12} 0}x fb 6526 b62 f0 a 4627543 cb a 59 a 24 b 9790 d0 f53 ec d 841 b 0 a d c 6 b a 0026 c a d f 77715$

```
1 function doWithdraw(address from, address to, uint256 amount) internal {
2
   // only use in emergencies!
 3
   // you can only get a little at a time.
 4
   // we will hodl the rest for you.
 5
 6
   require (amount <= MAX_WITHDRAWAL);
 7
    require(balances[from] >= amount);
 8
    require(withdrawalCount[from] < 3);
9
10 balances [from] = balances [from]. sub (amount);
11 // reentry point
12 to.call.value(amount)();
13 withdrawalCount[from] = withdrawalCount[from].add(1);
14 }
```

Figure 10: The code snippet of HODLWallet.

- 1. First, internal transactions triggered by this normal transaction create a loop that contains at least one *reentry point*. This detects the existence of reentrant function calls.
- 2. Second, there is *at least one internal transaction* that involves with the Ether or ERC20 token transfer. This rule is to remove transactions that do not cause any change to the Ether or ERC20 tokens. They are not real attacks since no financial benefits are achieved during this process.

Thanks to the query interface provided by the data aggregator, we can easily locate candidate transactions and remove unrelated ones. In total, we get 209, 227 candidate transactions.

Confirm the re-entrancy attack We further replay candidate transactions to confirm the re-entrancy attack at runtime. During this process, an analysis script is invoked. Our system first constructs a set of variables that could influence jump targets of the JUMPI opcode or values of transferred Ether. Thanks to the dynamic taint engine of our system, we can check whether a variable could influence the control flow by checking the taint tag of the second top value on the stack (taint.peekStack(1)). For each variable v in this set, we define the callback function for the SSTORE opcode to monitor whether the variable has been updated after the re-entrant point. If so, we will label the normal transaction as malicious.

Detection result EthScope locates 209, 227 candidate transactions. After replaying them, our system detected 2, 973 malicious normal transactions in the wild. Attackers are targeting 52 victim contracts, which are shown in Table-II in the link 13 .

We manually analyzed each detected attack. During the analysis, we only consider transactions that have caused financial loss as true positives (real attacks). Our analysis shows that 46 transactions are false positives, which are related to 4 victims (marked with * in Table-II). We show a detailed analysis of one false positive in the following.

Our system reported one attack targeting HODLWallet. However it is a false positive since it does not cause the financial loss. Fig. 10 shows the code snippet of the doWithdraw function. Specifically, the variable withdrawalCount[from] in line 8 influences the control flow. Also, this variable is updated after the reentry point in line 13. Thus, our system detects this as a re-entrancy attack. However, the transaction does not cause any financial loss since the balance balances[from] has been updated in line 10 (before the reentry point.) This is a false positive, though technically it is still a re-entrancy attack that targets withdrawalCount[from] instead of balances[from].

Since the DAO attack, the security community has paid lots of attentions to detect this vulnerability. However, the reentrancy attack still happened recently. Specifically, our system detected 579 re-entrancy attacks after the 9, 200, 000th block (Jan 2nd, 2020), in which 46 attacks are targeting Lend.Me [29] and 529 attacks are targeting Uniswap [30]. Both of them are DeFi applications. These two attacks caused significant financial loss.

Answers to Q2: With three different types of inputs, our system can help understand the suspicious transactions and further detect new attacks by locating and replaying candidate transactions. This demonstrates the effectiveness of our system to facilitate the attack investigation and detect new attack instances.

¹³https://github.com/Anonymouspaper146/SP2021fallsubmission.

	Block Range	# of Normal Transactions	Tools	# of Flagged Contracts	# of True Positives
0	-3,918,380	32,048,852	ECFChecker [39]	9	5
			Попреоре	# Flagged Normal Transactions	0
0	- 9,000,000	590,040,664	Sereum [47] EthScope	245, 519 2,392	2,347
				# Flagged Contracts	
0	- 8 180 000	500 930 221	SODA [33]	31	27
0	- 0, 100, 000	566, 556, 221	EthScope	29	27
				# Flagged Contracts	
0	4 500 000	78 141 399	ÆGIS [38]	7	7
0	- 4, 500, 000	18,141,322	EthScope	7	7
				# Flagged Contracts	
7.00	0 000 - 7 200 000	9 661 593	TXSPECTOR [28]	30	0
1,00	50,000 - 7,200,000	5,001,055	EthScope	1	1

Table 6: The comparison between our system and others in detecting the Re-entrancy attacks.

5.4 Comparison with previous systems

In this section, we compare our system with previous ones. We use the result of the re-entrancy attack since most systems can detect this attack. Table 6 shows the overall result. For each system, we use the same dataset and compare the detected attacks. The result shows that our system has lower false positives and false negatives.

ECFCHecker ECFCHecker [39] reports nine malicious smart contracts before 3, 918, 380th block (Jun 23, 2017). Among them, five are true positives and four are false positives. Our system detects six malicious smart contracts. All of them are true positives. Specifically, five false positives are the same smart contracts detected by ECFCHecker. One true positive ¹⁴ (a malicious smart contract in the 1, 743, 596-th block) is missed by ECFCHecker. Besides, our system does not flag the four false positives reported by ECFCHecker.

Sereum Sereum [47] has released the evaluation result for the first 9 million blocks on GitHub. It flags 245,519 normal transactions as re-entrancy attacks. Among the first 9 million blocks, 2,392 are detected by our system. Besides, among 2,392 normal transactions, 12 are not flagged by Sereum.

First, we manually confirm that these 12 normal transactions are true positives. That means they have been missed by Sereum. Second, for the 243, 139 normal transactions that are flagged by Sereum, we randomly pick up 10 transactions. The manual analysis shows that they are all false positives.

SODA For the first 8.18 million blocks, SODA [33] reports 31 vulnerable contracts, with 5 false positives and 26 true positives. After double-checking the 31 contracts, we find two of them are false positives ¹⁵ and one is true positive ¹⁶ (reported as the false positive by SODA.) Therefore, the result is 27 true positives and four false positives. EthScope detects the same 27 true positives.

ÆGIS ÆGIS [38] reports that seven smart contracts are victims of the re-entrancy attack during the first 4.5 million blocks. EthScope detects the same victimized smart contracts. However, ÆGIS marks fewer attacks transactions (1, 118 vs 2, 301) than EthScope. That's because ÆGIS limits their analysis to the first 10,000 normal transactions of each contract to reduce the execution time. Our system does not have this limitation, thanks to the efficient replay engine.

TXSPECTOR Due to the storage consumption, TXSPECTOR detects the re-entrancy attack from 7,000,000th block to 7,200,000th block. It flags 3,357 normal transactions as malicious and 30 vulnerable smart contracts. Among them, they manually labeled 17 ones as true positives. EthScope flags one malicious normal transaction ¹⁷ and one victim contract ¹⁸. It is the re-entrancy attack to SpankChain [1].

The authors of the TXSPECTOR kindly provide their dataset for us. We manually analyze the 17 smart contracts that are reported as true positives by TXSPECTOR. However, they are not vulnerable and cannot be victims of the re-entrancy attack according to our definition (causing a financial loss). Moreover, one true positive (the SpankChain re-entrancy attack) reported by our system is not detected by TXSPECTOR.

¹⁴0xf01fe1a15673a5209c94121c45e2121fe2903416

 $^{^{15} 0}x72f60eca0db6811274215694129661151f97982e, 0xd4cd7c881f5ceece4917d856ce73f510d7d0769e$

¹⁶0x59abb8006b30d7357869760d21b4965475198d9d

 $^{^{18} 0} x f 91546835 f 756 da 0 c 10 c f a 0 c da 95 b 15577 b 84 a a 7$

Answers to Q3: Comparing with previous systems, EthScope has lower false positives and false negatives when detecting the re-entrancy attack.

6 Discussion

The purpose of our system is to detect real attacks. Compared with other static analysis tools [32, 37, 41, 42, 43, 44, 46, 49, 50, 51], our system may miss some vulnerable smart contracts that *are not exploited in the wild*. Nevertheless, our system does not intend to replace existing static tools. Instead, these tools are complementary to our system. For instance, the vulnerable smart contracts reported by them [32, 37, 41, 42, 43, 44, 46, 49, 50, 51] could be one type of inputs (as shown in Section 5.2) to locate *real attacks*.

Though the main usage of our system is to perform investigation on attacks that have happened, it can be extended to conduct real-time detection of attacks. We can continuously monitor the blockchain state and use some heuristics to locate suspicious transactions. For instance, we can continuously monitor the transactions that are involved in bigamount Ether transfer. We can mark them as suspicious and understand the purpose of such transactions using our system. Another example is monitoring the transactions with smart contracts that may potentially be attacked, e.g., DeFi applications. That's because such applications are high-value targets for attackers to make profits. We leave the real-time detection of new attacks as one of the future work.

Though we have demonstrated the effectiveness of our system, an analyst still needs some public information as inputs, e.g., victim contracts. One potential direction is to use new techniques, e.g., machine learning algorithms to automatically locate suspicious transactions. Currently, our system provides a dynamic taint engine to facilitate the analysis. In the future, we can integrate more components, e.g., dynamic symbolic execution, into the system to ease the development of analysis scripts

7 Related Work

Data analysis frameworks of Ethereum Chen et al. [36] proposed a graph-analysis based approach to analyze Ethereum from different aspects, including money flow, account creation and contract invocation. DataEther [35] first instruments an Ethereum full node to collect data and then uses ElasticSearch [7] to store the collected data. Similar to EthScope, these systems can be used to locate suspicious transactions. However, they are not capable of introspecting the execution of smart contracts to understand and detect more attacks.

Static analysis tools of Ethereum smart contracts A number of static analysis tools have been proposed to detect vulnerabilities of Ethereum smart contracts, including Oyente [43], Mythril [16], Osiris [50], MAIAN [44], ContractFuzzer [41], ILF Fuzzer [40], Securify [51] and ZEUS [42]. These systems only provide a *static* view of smart contracts, i.e., whether they are vulnerable or not. They cannot provide a *dynamic* view of contract interactions (or transactions), which is useful to analyze and understand attacks. Our system does not intend to replace existing static tools. Instead, they are complementary to our system. For instance, the vulnerable smart contracts reported could be one type of inputs (as shown in Section 5.2) to locate *real attacks*.

Dynamic analysis tools of Ethereum smart contracts Dynamic analysis has been regarded as an effective complement to static analysis for security purposes. ECFChecker [39], Sereum [47], SODA [33] and ÆGIS [38] are representative tools to analyze Ethereum smart contracts. On one side, both Sereum [47] and ECFChecker [39] focus on the detection of the re-entrancy attack. On the other side, SODA [33] and ÆGIS [38] provide extensible interfaces to detect multiple types of attacks. Unfortunately, these tools suffer from the scalability issue. They are not suitable to perform the large-scale detection.

Pérez et al. [45] presented the first work that adopts the datalog-based approach to analyze vulnerabilities of smart contracts. However, it only analyzes transactions related to the smart contracts flagged by other tools. TXSPECTOR [28] also relies on datalog and supports customized rules to analyze different types of vulnerabilities and attacks. However, TXSPECTOR is not scalable to perform the large-scale detection, due to the heavy storage consumption.

Zhou et al. [26] investigated attacks in the wild. They leveraged internal transactions information (named *trace* in the paper) and transaction logs to measure six types of vulnerabilities, including call injection, re-entrancy, integer overflow, airdrop hunting, honeypot, and call-after-destruct. Our system has a different purpose. It focuses on building a scalable framework to understand and detect different types of attacks.

8 Conclusion

In this paper, we present the design of a scalable attack detection framework on Ethereum. It overcomes the scalability issue of existing systems that it can perform timely attack investigation and detect more attacks. We implement a prototype named EthScope and solve three technical challenges. The performance evaluation shows that our system can solve the scalability issue. The result with three different types of information as inputs shows that it can help an analyst understand attack behaviors and further detect more attacks.

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Figure 11: The trend graph of smart contract creation (a) and self-destruction (b). The y-axes show the total number of newly created smart contracts and destroyed ones for every ten days, respectively.

9 Appendix

9.1 Type-III Input: Abnormal Blockchain State

Besides the reported victim smart contracts and malicious transactions, an analyst can leverage the data aggregator to observe the blockchain state and use multiple heuristics to locate suspicious transactions. In the following, we elaborate the method of using the number of smart contract creation and self-destruction to locate suspicious transactions, and the process of understanding these transactions to detect multiple types of attacks.

9.1.1 Understand the attack

Some attacks may lead to abnormal blockchain state, which can be used by an analyst to perform the detection. In the following, we illustrate how our system leverages the abnormal blockchain state to detect attacks.

Locate suspicious transactions Attackers often create malicious smart contracts to automatically launch attacks. After that, they often destroy these contracts to save cost or hide traces. For instance, attackers of the bad randomness attack create a large number of smart contracts to lunch the attack and destruct them afterwards (Section 5.2).

Inspired by this observation, we draw a trend graph of smart contract creation and self-destruction shown in Fig. 11. From the figure, we can find that there exist several abnormal points where the numbers of new smart contracts (and destroyed ones) are much larger than those of the neighbors (marked with red circles in the figure).

These three abnormal points appear in blocks ranging from 2,000,000th to 3,000,000th, 6,500,000th to 7,500,000th and 8,900,000th to 10,110,000th, respectively. We use data aggregator to lookup transactions and accounts that create or destroy these smart contracts and label them as suspicious.

Understand suspicious transactions After analyzing suspicious transactions, we observe two types of attacks and an automated arbitrage trading behavior. We illustrate them in the following.

• *Suicide bomb DoS attack.* From blocks ranging from 2,000,000 to 3,000,000, there exists a smart contract ¹⁹ that contributes 34, 148 and 33,980 times of smart contract creation and self-destruction, respectively. The only functionality of the newly created smart contract is to self-destruct itself, and transfer its balance (1 Wei or 0 Wei) to a non-existent account.

We take a transaction 20 as an example to illustrate its purpose. Fig. 12(a) shows the dynamic call graph. The EOA (0x61d5ec) first invokes (index 0) a smart contract (0x7c2021) to create (index 1) a very simple contract (0x914374). Its functionality is to self-destruct itself, and transfer its balance (0 Wei in this example) to a non-existent account.

For simplicity, we only draw the first ten transactions, and this normal transaction actually triggered 320 times of self-destruction.

It is worth noting that, the destruction of a smart contract actually happens only when the execution of the normal transaction that initiates these internal transactions finishes (index 0). Thus, the contract 0x914374 can execute the

¹⁹0x7c20218efc2e07c8fe2532ff860d4a5d8287cb31

 $^{^{20}0}xa02be5a3f2687b68e4643e73d26c4661dc66fb3550aa34fc9-\ 6abfa4bcb0bf8b6$



Figure 12: The dynamic call graph of a *suicide bomb* DoS attack and an ERC20 airdrop hunting attack. Square: EOA, Circle: smart contract; Grey Box: attacker, Red Box: victim; Solid Line: transaction, Dotted Lines: ERC20 token transfer; The number before the opcode is the execution order for each opcode.



Figure 13: The trades in an arbitrage (normal transaction). The number in circle represents the execution order.

opcode SELFDESTRUCT multiple times before it is actually self-destructed. Moreover, according to the definition of the opcode SELFDESTRUCT, it will create a new EOA account (Section 2.1), without paying for the 25,000 gas charge ²¹, which is the gas needed to create a new account. These newly created accounts will consume lots of storage resources on the blockchain. This is called the *suicide bomb* DoS attack [34].

- Airdrop hunting attack. In blocks ranging from 6, 500, 000 to 7, 500, 000, there is a smart contract account ²² that contributes 501, 919 creation and 526, 079 times of smart contract creation and self-destruction, respectively. We randomly pick a normal transaction ²³, and draw the dynamic call graph in Fig. 12(b) to help us understand its purpose. As shown in the graph, the smart contract (0x7c2021) continually creates new smart contracts to transfer 2, 019.75 SEN tokens to the EOA (0xd48386) that initiates this transaction. The SEN token has an aggressive marking strategy, which will reward a few tokens for every *new* account that has made a transaction with SEN. This strategy is adopted by many token smart contracts. The purpose of creating so many *new* smart contracts is abusing this strategy to obtain rewards. Destroying these new smart contracts is not necessary but can save cost. This kind of rewards is usually called airdrop reward. Therefore, this attack is called *airdrop hunting* attack.
- Automated arbitrage trading. In blocks ranging from 8,900,000 to 10,110,000, there is a smart contract account ²⁴ that contributes 510,390 creation and 537,992 times of smart contract creation and self-destruction, respectively. After analyzing the suspicious transactions, we find this is a *trade bot*, which buys and sells digital assets among decentralized exchanges using arbitrage. Though this cannot be considered as an attack, this still shows the capability of our system to understand the behaviors of smart contracts.

²¹This vulnerability has been fixed in the EIP150 [9] hard fork of Ethereum

²²0xe9428d4a341ac20e9f2e6b95b12c9ad52733fcd9

 $^{^{23} 0}x5a5fb2f3d097c44d0454612404097eb51f0025bf86c5f25e1902639e139b944b$

 $^{^{24} 0} x 8018280076 d7 fa 2 ca a 1147 e 441352 e 8 a 89 e 1 d d b e$

Fig. 13 shows the digital assets transfer in an arbitrage (normal) transaction 25 , which includes two trades. The *trade bot* (0x801828) first exchanges 6.02048 PAXs [27] with 0.03474 Ether from Uniswap [30], and then exchanges 0.03821 Ether with 6 PAXs from Kyber [11]. As a result, the *trade bot* gets 0.003 Ether and 0.02 PAXs due to the exchange rate differences between the two exchanges Kyber and Uniswap.

We further analyze the purpose of the self-destruction of smart contracts. The *trade bot* first created lots of smart contracts in advance with lower gas price. When performing arbitrage, attackers will set up a higher gas price so that their trade transactions have a higher priority when being packed. That's because miners tend to pack transactions with higher gas price. After that, they self-destruct the smart contracts to receive the returned gas at a higher gas price since the current gas price used in the transaction is high.

9.2 Database Indices

Table 7 shows the database indices used in data aggregator. It is similar with the schema of the relational database.

 $^{^{25} 0}x3cf41ad4f703fe61368139b8482e75de53a335b9d76039ca071530bb5292b0c7$

Index Name	Field	Field of Nested Field	Field of Nested Field of Nested Field	Field of Nested Field of Nested Field of Nested Field
Block	Difficulty ^R ExtraData GasLimit ^R GasUsed Hash ^R Miner ^R Number ^R Timestamp ^R TxnCount			
	Transaction	CallFunction ^R ConAddress CumGasUsed FromAddress ^R GasLimit ^R GasPrice ^R GasUsed ^R GetCodeList ^R Hash ^R IntTxnCount Nonce ^R Status ToAddress ^R TxnIndex Value ^R		
		InternalTxns	CallFunction CallParameter ConAddress EvmDepth FromAddress GasLimit Output ToAddress TxnIndex Type Value	
		Logs	Address Topics Data	
		ReadCommittedState	Address Balance R CodeHash CodeSize Nonce	Key
		ChangedState	Address Balance Nonce Storage	Value Key
	Number		-	Value
	Timestamp			
Code	Transaction	Hash TxnIndex Input ^R	A 11	_
		Contract ^R	Address Hash Code	
	Timestamp			
State	Transaction	Hash TxnIndex Create Reset Suicide ^R		

Table 7: ElasticSearch Indices

^{*R*}: fields that are necessary for replaying transactions.