

# Front-Running Attack Benchmark Construction and Vulnerability Detection Technique Evaluation

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**Abstract**—Front-running attacks have been a major concern on the blockchain. Attackers launch front-running attacks by inserting additional transactions before upcoming victim transactions to manipulate victim transaction executions and make profits. Recent studies have shown that front-running attacks are prevalent on the Ethereum blockchain and have caused millions of US dollars loss. Vulnerable smart contracts, blockchain programs invoked by transactions, are held responsible for front-running attacks. Although techniques to detect front-running vulnerabilities have been proposed, their performance on real-world vulnerable contracts is unclear. There is no large-scale benchmark based on real attacks to evaluate their capabilities. This motivates us to build a benchmark consisting of 513 real-world attacks with vulnerable code labeled in 235 distinct smart contracts. We propose automated techniques to effectively collect real-world attacks and localize the corresponding vulnerable code at scale. Our experiments show that our approaches are effective, achieving higher recall in finding real attacks and higher precision in pinpointing vulnerabilities compared to the existing techniques. The evaluation of seven state-of-the-art vulnerability detection techniques on the benchmark reveals their inadequacy in detecting front-running vulnerabilities, with a low recall of  $\leq 6.04\%$ . Our further analysis identifies four common limitations in existing techniques: lack of support for inter-contract analysis, inefficient constraint solving for cryptographic operations, improper vulnerability patterns, and lack of token support.

**Index Terms**—blockchain, Ethereum, smart contract, vulnerability, front-running, empirical study, dataset, benchmark

## I. INTRODUCTION

Front-running [1] attacks in financial markets refer to the practice of leveraging knowledge of future transactions and

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```
1 contract TransferManager {
2   function relayOperation(ERC20 token, address user, bytes
      operation, bytes signature) {
3     if(verifySignature(user, operation, signature)){
4       require(checkUniqueness(user, operations, signature),"RM
      : Duplicate request");
5       executeOperation(operation);
6       // transfer relay fee to relayer
7       uint relayFee = getFee();
8       token.transferFrom(user, msg.sender, relayFee);
9   } }
```

Fig. 1. Simplified version of TransferManager contract [4] on Ethereum. Attackers attack by invoking relayOperation function before victim transactions.

trading before them to make profits. Front-running attacks also occur in blockchain systems like Ethereum [2]. Transactions on Ethereum are published before execution, meaning that upcoming transactions are available to all blockchain users, including potential attackers. By adjusting transaction execution orders with miners [3], malicious attackers can attack victims by executing transactions before victim ones so that the victim transactions would be executed on different blockchain states from what was expected. As a result, the attackers can make profits from the attack and cause financial losses to the victims.

Smart contracts, the programs invoked by transactions to perform actions on the blockchain, are held responsible for the attacks. Fig. 1 shows an example vulnerable smart contract. A relayer (`msg.sender`) provides a relay service for off-chain users to perform on-chain operations, and calls function `relayOperation` to execute user operations (Line 5). The relayer charges ERC20 [5] tokens (line 8) as the profits

of providing the service. Front-running attacks may occur since the users' operations and signatures used to invoke this contract are publicly available once the relayer submits the transaction. One attacker can invoke this contract before the relayer and take the profits, which should have been given to the relayer. As a consequence, the relayer's transaction fails since each user operation can only be executed once (line 4). The profits are taken by the attacker even if it is the relayer that provides the relay service.

Recent studies have revealed the prevalence and severity of front-running attacks on Ethereum by conducting measurement studies [3], [6], [7]. Torres et al. [7] found that front-running attacks are prevalent on the Ethereum blockchain and have caused a total loss of over 18.41M USD. Daian et al. [3] pointed out that front-running attacks also pose a major threat to the ecosystem and the consensus protocol of blockchain. Given the great impact, many researchers aimed to curb front-running in smart contracts. Vulnerabilities under front-running attacks have been named in different ways, such as transaction order dependency [8], event ordering bugs [9], and state inconsistency bugs [10]. In this paper, we refer to them generally as front-running vulnerabilities. Various techniques [8]–[13] have been proposed to detect such vulnerabilities in smart contracts. However, they have only been evaluated in terms of detection precision, leaving the recall unknown. There still lacks a large-scale systematic study to understand the performance and limitations of these techniques.

There are multiple challenges to addressing the research gap. First, a large-scale and representative benchmark with ground truth is needed. An existing empirical study [14] offers a benchmark with only four simple vulnerable contracts, with 33.75 lines of code in each on average, which is neither large-scale nor representative of real-world contracts. Second, it is still an open question how to locate the vulnerabilities from existing attacks and represent them in the benchmark. Unlike other vulnerabilities (e.g., Integer Overflow and Underflow [15]), front-running vulnerabilities are caused by the flawed design logic of contracts instead of a single line of coding mistakes. For example, the vulnerability in Fig. 1 is that the contract is designed to allow anyone to execute the user's operation. This design is meant to incentivize new relayers to join and ensure high availability of the relay service. However, such design incurs front-running attacks on relayers. Previous measurement studies made their efforts to collect attacks occurred in history, but their dataset did not pinpoint the vulnerability locations and thus is not usable as a benchmark to evaluate detection techniques.

To fill the research gap, we make the following contributions. First, we design an effective algorithm to comprehensively search for front-running attacks in the Ethereum transaction history. Second, we propose a novel approach to automatically localize vulnerable code from a historical attack. Third, we build a benchmark consisting of 513 real-world attacks with vulnerable code localized in 235 distinct contracts. Finally, we conduct an empirical evaluation on seven state-of-the-art vulnerability detection tools and investigate common

limitations of the techniques.

Our attack search algorithm enumerates all transactions in history with efficient pruning strategies and a generic attack model. Previous works [3], [7] rely on a limited number predefined patterns to find historical attacks, which can miss a great many attacks. Our evaluation results show that our algorithm can achieve 90.19% recall on a baseline dataset [7] and find 24.42x more attacks than the state-of-the-art technique. It also has precision as high as 98.69% since we strictly follow the definition of front-running. We search for historical attacks in the latest 800,000 blocks on the Ethereum mainnet and collect 188,700 attacks in total. With a large-scale dataset of real attacks, we continue to localize vulnerable code in smart contracts. For each attack, we consider blockchain shared data manipulated by the attacker as taint sources and perform dynamic taint analysis with the victim transaction. We consider the program location where victim profits are directly affected as the taint sink. Then we mark contract code executed along the taint flow trace from source to sink as vulnerable. Our manual analysis among three authors on a sample of attacks shows that the code localized by our approach can cover the exploited vulnerable contract logic in all attacks. In addition, we also find that our approach is precise and mark 99.66% less code than the baseline. In the end, we build a benchmark with 513 real-world attacks and identify the vulnerabilities in 235 contracts whose source code is available.

Based on the benchmark, we perform an empirical study to evaluate existing techniques and answer the following research question.

- How many vulnerabilities can existing techniques detect in our benchmark?
- What are the limitations of existing tools in detecting front-running vulnerabilities?

We conduct a systematic literature review on state-of-the-art works and select seven tools that implement techniques supporting front-running vulnerability detection. We use these tools to detect vulnerabilities in our benchmark. Our results show that existing tools have poor performance and can only detect vulnerabilities exploited by at most 6.04% attacks. We then investigate the limitations of the underlying techniques of each tool through manual analysis of samples of missed vulnerabilities. Our major findings include:

- Existing techniques can hardly perform precise inter-contract analysis, failing to capture many vulnerabilities involving cross-contract invocations.
- The wide use of cryptographic operations in contracts makes it difficult to generate concrete transactions using SMT solvers, limiting the capability of the techniques in exploring transaction executions.
- Vulnerability detection patterns of existing techniques are weak in capturing many front-running vulnerabilities.
- Many vulnerabilities are missed due to the negligence of profit making in tokens instead of Ethers.

## II. BACKGROUND

This section introduces the background knowledge of the Ethereum blockchain and front-running attacks. We base our presentation on Ethereum since it is the most popular blockchain that supports Turing-complete smart contracts [16]. In this paper, blockchain refers to the Ethereum blockchain unless otherwise specified.

### A. Ethereum State Transition Model

Ethereum blockchain can be considered a state machine [2]. State transitions occur when transactions get executed in new blocks mined by miners. A global state called *world state* is maintained by Ethereum. The blockchain world state comprises account cryptocurrency balances (in Ethers), smart contract code, and key-value mapping storage for each smart contract. Every executed transaction modifies the world state by performing a simple cryptocurrency transfer or invoking a smart contract, which is the program stored on the blockchain specifying the logic of world state modification. In order to achieve the consensus of state transitions across all blockchain miners, the execution of a transaction is deterministic given a pre-execution world state, and transactions are executed sequentially according to an order determined by miners. Miners hold the right to select transactions to execution and determine the execution order when a new block is mined.

### B. Front-running Attacks

Before execution, pending transactions are stored in a pool, broadcast to all miners, and known to attackers. Attackers can construct a malicious transaction based on the information revealed by a pending transaction and obtain profits by having miners execute the malicious transaction before the pending one. It results in a front-running attack where the victim transaction has an execution outcome different from that without the malicious transaction executed, causing loss to the victim transaction user.

Front-running can occur in traditional financial markets. For instance, in foreign exchange markets, malicious traders can leverage internal information about upcoming large EUR purchase orders, buy EUR using USD in advance at a lower price, and sell them back to USD afterward at a much higher price. As a result, the upcoming (victim) transaction buys EUR at a higher price, while the malicious traders (attackers) obtain profits from the price difference. Such markets are also implemented on the blockchain. Fig. 2 shows the simplified logic of a popular token exchange market, Uniswap [17], which contains front-running vulnerabilities and enables attacks similar to those in foreign exchange markets. The swap function sells the given amount of `tokenI` (line 23) and buys `token0` (line 24). The victim transaction swapping `tokenI` for `token0` can be attacked if the attacker invokes function `swap` in advance. The attacker's transaction will modify the values in variable `reserveI` and `reserve0` at line 22. As a result, the victim receives less `token0`, whose amount is computed at line 8, i.e., the victim buys `token0` at a higher price. The

```
1 contract Swap {
2   Pair tokenPair;
3   function swap(uint amountI) public {
4     (uint rI, r0) = tokenPair.getReserves();
5     amountI = amountI - 100gwei; // swap fees
6     (ERC20 tokenI,) = tokenPair.getTokens();
7     tokenI.transferFrom(msg.sender, this, 100gwei);
8     uint amount0 = rI * r0 / (rI + amountI) - r0;
9     logSwap(msg.sender, amountI, amount0);
10    tokenPair.doSwap(amountI, amount0); }
11  function logSwap(address u, uint in, uint out) {
12    (ERC20 tokenI, token0) = tokenPair.getTokens();
13    emit SwapEvent(user, tokenI, token0, in, out); }}
14 contract Pair {
15  uint reserveI, reserve0;
16  ERC20 tokenI, token0;
17  function getReserves() public returns(uint, uint){
18    return reserveI, reserve0; }
19  function getTokens() public returns(ERC20) {
20    return tokenI, token0;}
21  function doSwap(uint aI, uint a0) public {
22    reserveI += aI; reserve0 -= a0;
23    tokenI.transferFrom(tx.origin, this, aI);
24    token0.transferFrom(this, msg.sender, a0); }}
```

Fig. 2. Simplified version of UniswapV2 contract. Attackers invokes function `swap` before victims. Attackers can buy `token0` with `tokenI` at a lower price, and sell `token0` afterward at a higher price to make arbitrage.

attacker can later sell `token0` at a much higher price after the victim transaction to make profits.

Front-running is illegal in traditional markets regulated by the government. However, there is no similar governance on the blockchain. Attacks are much easier to launch since malicious users can easily know upcoming transactions from the public pool of pending transactions. Inserting attack transactions before victims is possible since the execution orders are determined by miners without any restrictions. Therefore, front-running attacks are prevalent on the blockchain and cause much damage [7], [7].

## III. RELATED WORKS

### A. Smart Contract Vulnerability and Detection

Researchers have identified many different types of vulnerabilities in smart contracts [18], including integer overflow/underflow, reentrancy, denial of service, and etc. Various techniques have been proposed to detect these vulnerabilities [8]–[12], [19]–[39]. Among them, we focus on those techniques capable of detecting front-running vulnerabilities in smart contracts. Oyente [8] was the first one detecting front-running vulnerabilities, by checking the existence of Ether transfer flows that are sensitive to transaction execution orders using symbolic execution [40]. Various follow-up techniques were proposed to enhance Oyente's performance. Ethracer [9] adopts dynamic symbolic execution to fuzz a smart contract with concrete transactions and checks whether the resulting blockchain world state is sensitive to the execution orders of these transactions. Mythril [12] and Conkas [13] leverage symbolic execution and static taint analysis [41] to detect front-running vulnerabilities by checking whether there are feasible execution paths where Ether transfers are affected by the taint sources whose contents can be modified by another transaction. Securify [11] uses abstract interpretation [42] to

match a contract with security property patterns, i.e., the receiver, amount, and path conditions of Ether transfers should not depend on variables that another transaction can manipulate. Similarly, Sailfish [10] builds the smart contract state dependency graph, summarizing the read-write dependencies between different public functions, which different transactions invoke. Then, the same security patterns of Securify are applied to the state dependency graph to detect vulnerabilities.

### B. Real-World Attacks and Measurement Study

Prior studies were conducted to understand the characteristics of front-running attacks and their prevalence in real-world smart contracts. Daian et al. [3] analyzed the transaction traffic on the Ethereum blockchain, showing that many arbitrage bots are competing with each other to perform front-running attacks on transactions submitted by ordinary users. Eskandari et al. [6] conducted a case study on four categories of smart contracts and found that front-running attacks could happen in contracts designed for cryptocurrency exchange markets, crypto-collectible games, gambling, and name services. From the case study, the authors identified three attack patterns, i.e., displacement, insertion, and suppression. Displacement attacks usually observe the input of a victim transaction, submit a transaction to take over the victim transaction, and obtain any profit that would be given to the victim transaction’s sender. The example contract in Fig. 1 is vulnerable to displacement attacks. An insertion attack is accomplished by two transactions. The first transaction is inserted before the victim transaction to alter the state at which the victim transaction is to be executed. The second transaction is submitted after the execution of the victim transaction to collect profits. The example attack in financial market mentioned in Section II-B is a typical insertion attack. A suppression attack is meant to attack time-sensitive transactions by filling the current block and delaying the victim transaction. Based on the findings from Eskandari et al., Torres et al. [7] took the first step to measure the real-world front-running attacks on Ethereum. They identified around 200 hundred thousand attacks from the blockchain transaction history and found that displacement and insertion attacks accounted for the majority, stealing an accumulated amount of 18.41M USD. Qin et al. [43] conducted a similar measurement study on the Ethereum blockchain, also showing that front-running attacks are prevalent and causing considerable financial loss.

## IV. ATTACK SEARCH AND DATASET

We aim to build a benchmark of vulnerable contracts from real-world front-running attacks. However, it is non-trivial to search for historical attacks given the large search space, and there exist no generic attack model to identify front-running attacks. This section introduces our attack model, based on which we propose an algorithm to effectively and comprehensively search for attacks in the blockchain transaction history.

### A. Attack Model

We model one front-running attack in blockchain transaction history with a tuple of transactions:  $\langle T_a, T_v, T_a^P \rangle$ , where  $T_v$

is the victim transaction being attacked, and  $T_a$  and  $T_a^P$  are transactions from the attacker. We define two transaction execution scenarios:

**Definition 1 (Attack Scenario)** *The tuple of transactions are executed in the order  $T_a \rightarrow T_v \rightarrow T_a^P$ .*

**Definition 2 (Attack-Free Scenario)** *The tuple of transactions are executed in the order  $T_v \rightarrow T_a \rightarrow T_a^P$ .*

The attack scenario refers to the execution order in the blockchain history where the attack occurred. The attack-free scenario refers to the execution order without interference from attackers, which was intended by the victim.

We consider  $A = \langle T_a, T_v, T_a^P \rangle$  as a front-running attack if it satisfies two properties:

**Property 1 (Attacker Gain)** *The attacker obtains financial gain in the attack scenario compared with the attack-free scenario.*

**Property 2 (Victim Loss)** *The victim suffers from financial loss in the attack scenario compared with the attack-free scenario.*

The intuition of our attack model is that the attacker should steal benefits from the victim by inserting  $T_a$  and manipulating the world state on which  $T_v$  executes. The Attacker Gain property specifies that the attacker benefits from front-running victim transactions. The Victim Loss property specifies that the victim is harmed by the attack. Note that attackers may have other incentives besides financial gains to launch a front-running attack. We do not consider such attacks in this work because such incentives are hard to validate.

$T_a^P$  is optional to perform an attack. Eskandari et al. [6] found that attackers may or may not need to execute another transaction after  $T_v$  to collect profits (Section II-B). If  $\langle T_a, T_v \rangle$  already satisfies the above attack properties, it is considered as an attack without  $T_a^P$ . Moreover, attackers may insert multiple transactions before and after  $T_v$ , but we assume attackers are rational blockchain users who would merge multiple consecutive transactions into a single one to reduce transaction fees.

### B. Attack Search

Existing measurement studies attempt to search for attacks using predefined patterns of transaction data or execution traces to characterize attacks [3], [7]. For instance, they consider transactions that copy the data of another transaction as attacks or search for transactions swapping tokens in the same way as described in Fig 2 in a limited number of already known vulnerable token exchange contracts. As proposed below, we do not rely on any predefined patterns and search for attacks comprehensively in the transaction history by enumerating all possible transaction combinations and identifying attacks based on our attack model.

Algorithm 1 shows the attack search procedure in a transaction history, which is represented as a sequence of transactions  $\mathbb{T}$ . It searches for the combinations of historical transactions

**Algorithm 1:** Search for attacks in transaction history.

---

**Input** : a sequence of transactions executed in history  $\mathbb{T}$   
**Output**: a set of historical attacks  $\mathbb{A}$

```

1  $\mathbb{A} \leftarrow \emptyset$ ;
2 for  $i_a \leftarrow 0$  to  $|\mathbb{T}| - 1$  do
3    $T_a \leftarrow \text{getTransactionAtIndex}(\mathbb{T}, i_a)$ ;
4   for  $i_v \leftarrow i_a + 1$  to  $|\mathbb{T}| - 1$  do
5      $T_v \leftarrow \text{getTransactionAtIndex}(\mathbb{T}, i_v)$ ;
6     if  $\text{shouldPrune}(T_a, T_v)$  then continue;
7     if  $\text{isAttack}(T_a, T_v)$  then
8        $\mathbb{A} \leftarrow \langle T_a, T_v \rangle$ ;
9       continue;
10    end
11    for  $i_p \leftarrow i_v + 1$  to  $|\mathbb{T}| - 1$  do
12       $T_a^p \leftarrow \text{getTransactionAtIndex}(\mathbb{T}, i_p)$ ;
13      if  $\text{shouldPrune}(T_a, T_v, T_a^p)$  then continue;
14      if  $\text{isAttack}(T_a, T_v, T_a^p)$  then
15         $\mathbb{A} \leftarrow \langle T_a, T_v, T_a^p \rangle$ ;
16        continue;
17      end
18    end
19  end
20 end

```

---

that satisfy the attack model. The key idea of the search algorithm is that a successful front-running attack must result in a transaction sequence in the transaction history matching the attack scenario ( $T_a \rightarrow T_v \rightarrow T_a^p$ ). We can then generate and execute its corresponding attack-free scenario ( $T_v \rightarrow T_a \rightarrow T_a^p$ ) to validate whether the transaction sequence satisfies our two attack properties defined in Section IV-A. We consider every transaction in the history as a potential  $T_a$  (line 2) and then search for any subsequent transaction  $T_v$  (line 4) that was successfully attacked by  $T_a$ . Function `isAttack` executes the given transactions in the attack and attack-free scenarios and checks whether the execution result satisfies the two properties. As explained, an attack can be accomplished by two or three transactions. If the attack properties based on the two execution scenarios can be satisfied by  $T_a$  and  $T_v$ , it is an attack by two transactions. Otherwise, the algorithm continues to search in subsequent transactions for the third transaction  $T_a^p$  (line 11) such that  $\langle T_a, T_v, T_a^p \rangle$  forms an attack.

In `isAttack` function, we consider the transaction sender of  $T_a$  and  $T_v$  as the attacker and victim, respectively. Given that many attackers use bot contracts [7] to perform attacks, we also consider the first contract that  $T_a$  invokes as the attacker. To check the financial gain and loss of attackers and victims, we consider Ether, the native cryptocurrency on Ethereum, as well as four popular token standards as quantitative financial profits, namely ERC20 [5], ERC721 [44], ERC777 [45], and ERC1155 [46]. Financial gain or loss is determined using the difference in the amount of digital assets that the attacker or victim receives in two transaction execution scenarios.

Executing transactions in attack and attack-free scenarios is expensive. Therefore, we make two improvements to the algorithm efficiency without missing attacks. First, we consider existing execution in the blockchain history as the attack scenario in the `isAttack` function so that the execution result of the attack scenario is already available. We only need to

TABLE I  
NUMBER OF ATTACKS IN BASELINE DATASET THAT CAN BE FOUND BY OUR  
ATTACK SEARCH ALGORITHM.

	Displacement	Insertion	Suppression
Baseline	2,983	196,691	50
Ours	2,910	177,222	0

execute transactions in the attack-free scenario. Second, we verify the necessary conditions of the attack properties in the `shouldPrune` function and prune the search space early if the conditions are not satisfied without missing any attacks. The primary necessary condition is that  $T_a$  and  $T_v$  must have read-write conflicts [47] on some shared data in the blockchain world state [48], i.e., the account balance, contract code, and contract storage. Inferring from the execution trace in the blockchain history, we consider  $T_a$  and  $T_v$  have read-write conflicts if  $T_a$  modifies the same shared data that  $T_a$  performs a def-clear [49] read. Otherwise, the execution outcome of  $T_a$  and  $T_v$  is irrelevant to the order between them, and the attack properties will not be satisfied. In addition, we also prune the search space if  $T_a$  and  $T_v$  are submitted by the same account.

### C. Front-Running Attack Dataset

We use our attack search algorithm to search for front-running attacks in the block range 13,000,000-13,800,000, which are the latest 800,000 blocks when this study was conducted (Dec. 2021). We split the entire blockchain history into windows of three blocks and slide the window with an offset of one block. In the range of history that we are about to analyze, there are 799,998 block windows. In each window, transactions in the consecutive blocks are concatenated into one sequence and we search for attacks in this sequence with Algorithm 1. We analyze 16 block windows in parallel, and the search timeout in each block window is one minute. The search is performed on a CentOS 8 machine with an AMD Ryzen 3975WX CPU and 512GB RAM. The average time used to search one block window is 7.51s. We do not search attacks in the entire blockchain history because the contracts exploited by older attacks may no longer be active. Although the average search time of searching each block window is only around half of the average Ethereum block interval (15s) [50], it is also impractical to search the entire Ethereum history. In the end, we obtain the dataset  $\mathbb{D}^A$ , comprising 188,700 attacks, from the search.

### D. Attack Search Evaluation

To ensure the quality of dataset  $\mathbb{D}^A$ , we evaluate our attack search algorithm by answering RQ1:

- **RQ1:** Is our search algorithm effective in finding attacks?
  - **RQ1-1:** Can our algorithm effectively find real attacks?
  - **RQ1-2:** Can our attack model effectively characterize attacks?
  - **RQ1-3:** Can our algorithm outperform the state-of-the-art attack search technique in finding attacks?

**Methodology:** To evaluate the algorithm’s precision in RQ1-1, we manually analyze 383 attacks ( $\mathbb{D}^S$ ), which are randomly

sampled among all attacks ( $\mathbb{D}^A$ ) to achieve 5% confidence interval. To facilitate manual analysis, we only sample those attacks whose invoked smart contracts have source code available. Three authors individually analyze the execution traces of each transaction in each sampled attack, interpret the semantics of underlying smart contracts, and check whether each attack found by our algorithm is an actual front-running attack according to the attack definition [18], [51]. Disagreements are solved by discussions among authors until consensus is reached. To answer RQ1-2 and RQ1-3, we consider the measurement study conducted by Terres [7] as the baseline, which proposes an approach searching historical attacks using predefined transaction patterns for displacement, insertion, and suppression attacks, respectively (Section III-B). Baseline offers a dataset of three categories of attacks, as shown in the first row of Table IV-D. To answer RQ1-2, we apply our attack algorithm to search for all the attacks in the baseline dataset and check if our model can capture those attacks. For RQ1-3, we apply our algorithm to search in the latest 1,000 blocks (block number 11,299,000-11,300,000, containing 175,552 transactions) that the baseline searched and check whether our algorithm can find more attacks.

**Results:** For RQ1-1, there are only five falsely reported attacks, giving 98.69% precision. All of them are caused by the inappropriate attack-free scenario execution. In blockchain history, there could be many other transactions between  $T_a$ ,  $T_v$ , and  $T_a^p$ . When we change the transaction orders to mimic attack-free scenarios, the relative orders between  $T_a$  (or  $T_v$ ) and other transactions are also changed. Financial profits of the attack or victim could be affected by such relative orders. As a result, the financial profits in the attack-free scenario could be incorrectly calculated, and false-positively reported attacks may be induced, but our manual check shows that such cases are rare.

Table IV-D shows the experiment results for RQ1-2. Out of the total 199,724 attacks in the baseline, our attack model can identify 90.19% (180,125), indicating the generality of our attack model. We further investigate the reasons for missed attacks. Among the three types of front-running attacks collected by the baseline, all the suppression attacks involve multiple attack transactions before the victim transaction, which do not fit our attack model. This is not a significant flaw in our attack model since suppression attacks only comprise a tiny portion (0.03%) of all attacks. We sample 61 out of 73 and 377 out of 19,469 (95% confidence level, 5% confidence interval) missed displacement attacks and insertion attacks, respectively. We find that 215 attacks are missed because our model is more conservative and stricter than the patterns used by the baseline. For instance, two transactions compete to buy the same NFT token with ERC20 tokens, and only one of them will succeed. The baseline considers such case as an attack. However, it is unknown whether the NFT token is worth more than the paid ERC20 tokens, so our model does not consider it an attack. In 160 cases, the attacker obtains zero profits or loses profits in the attack scenario. For 19 missed attacks, we cannot re-execute the transactions in the attack-free scenario due to a

violation of blockchain protocol (e.g., transaction nonce, block limit, etc.). Thus our algorithm does not report these attacks. The rest 44 missed cases are caused by the inappropriate attack-free scenario execution as described in the previous paragraph.

In the experiment for RQ1-3, the baseline is able to find 277 attacks in the block range, while our algorithm is able to find 6,765 attacks, 24.42x more. All the attacks found by the baseline can be found by our algorithm. This result shows that our algorithm has a much higher recall rate in finding attacks. This is because our algorithm comprehensively enumerates transactions in the blockchain history instead of relying on the heuristic patterns like the baseline.

*Answer to RQ1:* Our attack search algorithm can effectively find 24.42x more attacks than those by baseline with 98.69% precision. The effectiveness of our search algorithm ensures the quality of dataset  $\mathbb{D}^A$ , which serves as a basis in the following empirical study.

## V. VULNERABILITY LOCALIZATION AND BENCHMARK

While Section IV-C describes the construction of the dataset  $\mathbb{D}^A$  for front-running attacks, the dataset cannot be used directly to evaluate various techniques' performance in front-running vulnerability detection. Each entry in  $\mathbb{D}^A$  is an attack consisting of two or three transactions but it does not pinpoint the vulnerable code snippet(s), which provide essential information to validate if vulnerabilities are correctly detected. In this section, we present our approach to localize the vulnerable code snippets from the transactions.

### A. General Ideas in a Nutshell

Pinpointing the vulnerable code snippet(s) responsible for an attack is an open problem. In many cases, it could be the overall logic design of the vulnerable contract instead of a single line of code or a function. For instance, in Fig. 2, it is the algorithm design, which calculates the exchange rate of tokens, that enables front-running transactions. None of the three functions alone is vulnerable without considering the logic of the other two. In this example, the attack transaction  $T_a$  can call the swap function (Line 3) before the victim transaction  $T_v$ , reducing the amount of swapped tokens obtained by  $T_v$ . A naive approach is to consider all the code in Fig 2 executed by  $T_v$  in an attack scenario to be vulnerable. However, this approach is too coarse and may falsely consider a large portion of code as vulnerable. The code at Line 5-7 to pay a constant swap fee, and the body of function `logSwap` invoked at Line 9 are falsely marked vulnerable, although they are unrelated to the vulnerable logic to compute the amount of swapped tokens.

This motivates us to devise a more accurate mechanism that can scale to the large dataset  $\mathbb{D}^A$  to localize vulnerable code. In a nutshell, our approach identifies the blockchain data accessed by the victim transaction  $T_v$  but altered by the attack transaction  $T_a$  (*attack altered data*), and performs a dynamic taint analysis [41] with  $T_v$  using attack altered data as taint sources and considering taint sinks the program location where



profits earned by the victim are directly affected. We extract the taint flow trace from source to sink and consider contract code executed along this trace as vulnerable. Specifically, the attack altered data of an attack is defined as follows:

**Definition 3 (Attack Altered Data)** *The attack altered data in an attack  $A = \langle T_a, T_v, T_p \rangle$  is the blockchain data that  $T_v$  performs a def-clear read after the data has been stored by  $T_a$  in the attack scenario.*

In Fig 2,  $T_a$  invokes function `swap` modifying contract variables at line 22, which are later loaded by  $T_v$  at line 18 through line 4. We consider these two variables as taint sources in the dynamic taint analysis of  $T_v$ . Profits earned by the victim are transferred at line 24, whose amount is decreased because of the attack. We thus consider line 24 as the taint sink. We then compute the vulnerable code snippet by extracting the flow from source to sink, i.e., line  $18 \rightarrow 4 \rightarrow 8 \rightarrow 8 \rightarrow 24$ . The vulnerable logic that computes the token exchange rates using attack altered data is identified, while contract code at line 5-7 and `logSwap` function are excluded. Compared with the naive approach, which marks all 14 lines of code, we only mark five lines in function `swap`, `logSwap`, `getReserves`, and `doSwap` as vulnerable.

### B. Localize Vulnerability with Influence Trace

Now we present how to mechanically localize vulnerable code snippet(s) from an attack  $A = \langle T_a, T_v, T_a^p \rangle$ . First, we localize the taint sources by identifying attack altered data in the attack scenario. Blockchain shared data, i.e., account balances, contract code, and contract storage, which are modified in  $T_a$  and read without preceding writes in  $T_v$ , is considered as attack altered data. Those operations in  $T_v$  that perform def-clear reads on attack shared data are considered as taint sources. Second, we localize the taint sink that is held responsible for the loss of victim’s financial profits. We conduct a manual analysis on the same set of attack samples  $\mathbb{D}^S$  as in Section IV-D and check how victims’ financial profits are influenced by attack altered data. We make an interesting finding that *all attacks can be summarized into three attack patterns* based on how the attack altered data influences victim transactions, namely Path Condition Alteration, Computation Alteration, and Gas Estimation Griefing. Taint sinks are defined accordingly for different attack patterns.

#### Path Condition Alteration:

```
1 if (altered(sharedData)) {
2   uint profit = computeProfit();
3   victim.transfer(profit);
4 }
```

The above code snippet shows the first attack pattern. The victim’s profit depends on a path condition evaluated using attack altered data. The example showing in Fig 1 falls into this pattern. In this pattern, the root cause is that the path condition is manipulatable by attackers, while the computation of profits is not. We consider the conditional statement as the taint sink. Note that we cannot use the profit transfer operations as taint

sinks since they do not necessarily data-depend on the attack altered data.

#### Computation Alteration:

```
1 uint profit = calculateProfits(altered(sharedData));
2 victim.transfer(profit);
```

The above code snippet shows the computation alteration pattern. The computation of the victim’s financial profit is manipulated without changing the execution path. Attacks on the example exchange contract in Fig 2 falls into this pattern. We consider the statement that transfers profits to the victim as the taint sink.

#### Gas Estimation Griefing:

```
1 parameterizedExpensiveOperation(altered(sharedData));
2 victim.transfer(profit);
```

Gas estimation griefing is different from the previous two patterns. Instead of manipulating the execution path or computation outputs, the attacker attacks by leveraging the gas model of Ethereum. Gas is a measure of computing resources consumed during transaction execution. Blockchain users need to specify a sufficient gas limit before submitting transactions, otherwise the execution fails. The gas consumption of transactions may depend on the attack altered data, in which case attackers can make the actual gas consumed by the victim transaction larger than the user specified limit. As a result, attackers could make victim transaction fail to his own benefits. Note that the underlying smart contracts may not contain vulnerabilities because the attack will not succeed if the victim transactions are equipped with sufficient gas. Therefore, we do not define taint sink or localize vulnerabilities for gas estimation griefing attacks.

We classify the attack  $A$  into attack patterns by inspecting the execution traces of  $T_v$  in the two execution scenarios, and identify the taint sink  $\delta$  accordingly. Let  $\tau$  and  $\tau^f$  denote the two execution traces of  $T_v$  in the attack and attack-free scenarios, respectively. If  $\tau$  throws an out-of-gas exception while  $\tau^f$  does not,  $A$  is considered a gas estimation griefing attack and excluded from our vulnerability localization. To classify the attack to the other two patterns, we first extract the sequences of program locations performing digital asset transfers in  $\tau$  and  $\tau^f$ , and denote them as  $[\tau_0, \tau_1, \dots, \tau_p]$  and  $[\tau_0^f, \tau_1^f, \dots, \tau_q^f]$ , respectively. We distinguish the attack patterns of an attack by checking the proper prefix of  $\tau$  and  $\tau^f$ .

Case 1 (Path condition alteration):  $\exists i, 0 \leq i \leq \max(p, q)$  such that  $\tau_i \neq \tau_i^f$  and  $\forall j, 0 \leq j < i \wedge \tau_j = \tau_j^f$ . We categorize attack  $A$  as a path condition alteration attack, and consider the first divergence point between  $\tau$  and  $\tau^f$  as  $\delta$  for this attack, where  $\tau_i$  and  $\tau_i^f$  control-depend on  $\delta$ .

Case 2 (Computation alteration):  $\forall i, 0 \leq i \leq \max(p, q) \wedge \tau_i = \tau_i^f$ . We categorize attack  $A$  as a computation alteration attack. Note that there must exist  $j, 0 \leq j \leq \max(p, q)$ , such that the transfer operation at  $\tau_j$  (or  $\tau_j^f$ ) transfers different amount of digital assets. We consider the program location  $\tau_j$  as  $\delta$  for this attack.

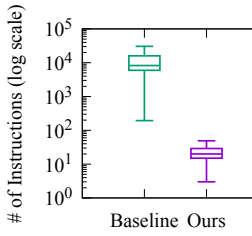


Fig. 3. Distribution of the number of EVM instructions marked as vulnerable by the baseline and our approach for each attack in  $\mathbb{D}^S$ .

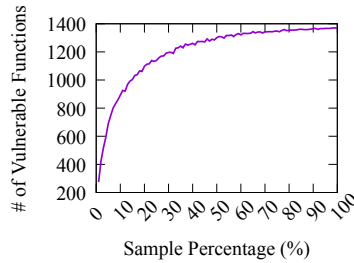


Fig. 4. The total number of distinct vulnerable functions in top-1200 contracts saturates as more attacks are sampled from  $\mathbb{D}^P$ .

Finally, we extract the flow trace from taint source to sink. We call this flow trace *influence trace*, covering the code that depends on attack altered data and influences the victim’s financial profits. Note that for one attack, there can be multiple taint sources and thus multiple influence traces since the attack altered data may be loaded as tainted values in different places. We use influence traces to over-approximate the vulnerability location of an attack by considering all code executed in an influence trace as vulnerable. It is a trade-off between localizing a smaller range of vulnerable code and ensuring the vulnerability is covered by the marked code, because it is hard to precisely and correctly localize without contract specifications from developers.

### C. Vulnerability Localization Evaluation

We evaluate the effectiveness of our vulnerability localization approach with the following research question:

- **RQ2:** Can our approach precisely identify the exploited vulnerabilities from real-world attacks?

**Methodology:** We answer RQ2 from two aspects with the dataset  $\mathbb{D}^S$  as mentioned in Section IV-D. First, we check that given a real-world attack, whether the exploited vulnerability can be localized by our approach. We perform a manual analysis on each attack in  $\mathbb{D}^S$ . The five falsely reported attacks identified previously are excluded. For each attack, three authors individually check whether the underlying vulnerable contract logic can be covered by the vulnerable code identified by our approach. We discuss all disagreements until they are resolved. Second, we check whether our approach can precisely pinpoint vulnerable code without including many unrelated code. We build a baseline based on the naive approach mentioned in Section V-A. We collect and compare the number of EVM instructions identified as vulnerable code by the baseline and our approach, respectively. We measure how many unrelated code our approach can reduce compared to the baseline.

**Results:** In our manual inspection, we find that the identified vulnerable code is able to cover the vulnerable logic exploited in all 378 attacks of  $\mathbb{D}^S$ . On average, 25.25 EVM instructions are marked vulnerable for each attack. Compared to the baseline, our approach marks only 0.34% of the those instructions

marked by the baseline as vulnerable, resulting in a 99.66% reduction rate. One can leverage our approach to construct effective and large benchmarks on front-running vulnerabilities in the absence of contract specifications.

*Answer to RQ2:* Our localization approach is effective in pinpointing vulnerable code to a much smaller range than the baseline without missing any exploited vulnerabilities.

### D. Benchmark Construction

To build a benchmark for the comparison of vulnerability detection tools, we extract influence traces for each attack in dataset  $\mathbb{D}^A$ . Attacks that result in multiple influence traces are excluded to avoid ambiguities in vulnerability localization. We mark all public contract functions that are executed in the influence traces as vulnerable. We label vulnerable functions because the contract analyzers evaluated in Section VI commonly report problems at the function level.

We do not have the ground truth of all vulnerabilities in each contract. For each contract included in the benchmark, we are unsure if our benchmark has labeled most of the vulnerabilities ever exploited in blockchain history, because we did not search the entire blockchain history in Section IV-C. To mitigate this threat, we focus on a set of most popularly attacked contracts and check if additional vulnerabilities in these contracts can be labeled when more attacks in the blockchain history are considered.

The following strategy is adopted for benchmark construction. We select top- $N$  popularly attacked contracts and only consider vulnerable functions in these contracts in our benchmark. The popularity is measured by the invocation frequency of each contract in all the influence traces of all attacks in dataset  $\mathbb{D}^A$ . From  $\mathbb{D}^A$ , we select a subset  $\mathbb{D}^P$  of attacks whose influence traces only involve contracts in these top- $N$  contracts. Then,  $n\%$  attacks are sampled from  $\mathbb{D}^P$ . We increase  $n$  from 1 to 100 with step 1 and compute the number of distinct vulnerable functions localized in each sample. If the total number of distinct vulnerable functions saturates as  $n$  increases, it indicates that we are unlikely to find new vulnerable functions in these top- $N$  contracts even if we keep searching for more attacks in the blockchain history. In other words, the occurrence of saturation hints that exploited vulnerable functions in the selected contracts have been mostly labeled. Intuitively, we want to include more contracts in the benchmark while saturation is observed. In our study, we set  $N$  to 1200. Fig. 4 shows the total number of distinct vulnerable functions against the sampling size of  $\mathbb{D}^P$ . The number of vulnerable functions only increases by 0.36% (from 1,365 to 1,370) between 90% and 100% samples. The saturation would gradually disappear when the number of contracts considered increases beyond 1,200.

Therefore, we build benchmark  $\mathbb{B}^A$  on the 1,200 selected contracts by analyzing the attacks in dataset  $\mathbb{D}^P$ . Vulnerable functions in these contracts are labeled with influence traces,



as previously explained for each attack. In addition, we also use influence traces to remove those attacks that exploited the same vulnerability. If multiple attacks have the same influence trace, we consider that they are duplicate exploitation and include only one of them. To facilitate manual analysis, we include only those attacks occurring at the functions whose source code is available on Etherscan [52]. As a result, we construct the benchmark  $\mathbb{B}^A$  consisting of 513 attacks with vulnerable functions localized in 235 distinct contracts.

## VI. EVALUATION OF EXISTING TOOLS

In this section, we demonstrate the use of  $\mathbb{B}^A$  to understand the status quo of front-running vulnerability detection. We evaluate tools that implement state-of-the-art vulnerability detection techniques and answer the following research question.

- **RQ3:** How many vulnerabilities can existing tools detect in our benchmark?

### A. Tool Selection

We conduct a systematic literature review to collect tools that implement representative state-of-the-art smart contract analysis techniques detecting front-running vulnerabilities. Based on the guideline from Brereton et al. [53], we search for related publications in top-tier conferences and journals, perform a backward snowballing to find more literature, and collect available tools from them. To largely include the state-of-the-art tools, we use *contract*, *ethereum* as search keywords and search for publications in all CORE [54] A/A\* ranked venues in software engineering and security fields with research code: 4612, 4604, and 0803. For each matching publication, we read the abstract and apply the following criteria: 1) Empirical studies and literature reviews are excluded. 2) Only papers about detecting contract vulnerability without requiring additional information from developers are included. At this step, we are able to collect 47 publications in 18 venues. We continue to perform a backward snowballing by searching for related literature in the references of these publications. In the end, we find 17 additional papers, technical reports, and GitHub repositories. From these literature, we collect available tools, which implement the techniques that support the detection front-running vulnerabilities. In the end, we collect seven tools suitable for our empirical evaluation, namely Oyente [8], Securify [11], Ethracer [9], Mythril [12], Conkas [13], Securify2 [55], and Sailfish [10]. The techniques used in these tools are discussed in Section III-A.

### B. Experiment Design

For each attack in benchmark  $\mathbb{B}^A$ , we run experiments to check whether the exploited vulnerability can be detected by each tool. We use each tool to analyze all contracts whose code is marked vulnerable in  $\mathbb{B}^A$ . Note that none of the selected tools support analyzing a group of contracts together, so we let each tool analyze contracts individually. Two tools, i.e., Securify2 and Sailfish, can only analyze contracts in source code in a single file. We use Hardhat [56] toolchain to flatten contract source code into a single file and let these

TABLE II  
VULNERABILITY DETECTION RESULT OF EACH TOOL ON BENCHMARK  $\mathbb{B}^A$ .

Tool	Attacks			Contracts <sup>1</sup>		
	TP	FN	Recall	N/A <sup>2</sup>	Timeout	Failure
Oyente	0	513	0%	0	0	0
Mythril	16	497	3.12%	0	0	20
Conkas	0	513	0%	0	4	205
Securify	31	482	6.04%	0	0	69
Ethracer	13	500	2.53%	0	1	4
Securify2	0	513	0%	23	0	206
Sailfish	8	505	1.56%	23	1	186

<sup>1</sup> There are in total 235 distinct contracts involved in all influence traces of attacks in  $\mathbb{B}^A$ . One distinct contract may be involved in influence traces of multiple attacks.

<sup>2</sup> The contract is not compilable for tools that analyze bytecode, or not flattenable for tools that analyze source code in single file.

two tools analyze the flattened source file. For all other tools that analyze contract bytecode, we compile the contract source code into Byzantium EVM bytecode [57], which is the most compatible version supported by all tools. Different tools may detect various types of vulnerabilities. However, we are only interested in the result of front-running vulnerability, i.e., event ordering bugs in Ethracer and transaction order dependency in all other tools.

We set the analysis timeout of each tool equally to three hours, which is larger than the longest timeout among the evaluation experiments of these tools' original papers. With benchmark  $\mathbb{B}^A$ , we adopt the following approach to check whether a vulnerability exploited by an attack is detected by each tool. In the detection results of one tool, we consider one attack is *true positive (TP)* if the tool reports problems in any of the vulnerable functions localized with this attack as described in Section V-D. If none of these functions is reported vulnerable by the tool, we consider the attack is *false negative (FN)*. The recall rate of each tool is computed with the total number of TP attacks divided by the total number of attacks in  $\mathbb{B}^A$ . Note that our benchmark does not label vulnerable functions that have not been exploited in the blockchain history. If one tool reports problems in other functions outside our benchmark, we cannot conclude whether they are false alarms or not. Thus, we do not evaluate the precision of these tools.

### C. Evaluation Results

Table II shows the vulnerability detection result of each tool. On the left side, we report the number of TP and FN attacks for each tool using the criteria mentioned in Section VI-B. For all tools, the number of missed vulnerabilities is significant. The best tool, Securify, only has a 6.04% recall rate. The majority of vulnerabilities are missed by all tools. Our evaluation shows the poor performance of state-of-the-art tools with a large-scale benchmark. A similar conclusion was drawn by the previous study [14] with a small benchmark of four contracts, which are not representative since the average lines of code for each contract is only 33.75, and none of them is real-world contract used on the blockchain. In comparison, our benchmark con-

TABLE III  
MANUAL ANALYSIS RESULTS FOR THE LIMITATIONS OF EACH TOOL.

Tool	FN Attacks		Limitation				Unknown <sup>2</sup>
	Total	Sample	Code IC <sup>1</sup>	Analysis CS <sup>1</sup>	Oracle P <sup>1</sup>	T <sup>1</sup>	
Oyente	390	194	124	-	65	5	0
Mythril	370	189	132	-	52	5	0
Conkas	12	12	7	-	5	0	0
Securify	155	155	0	-	0	155	0
Ethracer	491	216	133	31	19	0	33
Securify2	3	3	0	-	0	3	0
Sailfish	47	47	41	-	0	6	0

<sup>1</sup> IC, CS, P, and T stand for Lack Support for Inter-Contract Analysis, Constraint Solving for Cryptographic Operations, Weak Detection Pattern, and Lack of Token Support, respectively.

<sup>2</sup> We were unable to identify the limitations resulting in 33 FN attacks for Ethracer.

tains much more representative vulnerable contracts and can better reveal the real performance of vulnerability detection techniques.

We also found that several tools could not successfully analyze many contracts, as shown on the right side of Table II. Some tools timeout on the analysis of a few complex contracts, as shown in the Timeout column. Securify2 and Sailfish work on Solidity source code and can only analyze contracts written in a single file. The source code of 116 out of 235 contracts in our benchmark spreads across multiple files. Although we try to flatten multi-file contracts into a single file, there are 23 contracts that can not be flattened, as shown in the N/A column. In addition, we also found that Securify2 and Sailfish have poor support for contracts written in newer Solidity versions, resulting large amount of analysis failure. We found that other bytecode analyzers, especially Conkas, crash on a large portion of contracts. Similar crashes are encountered by other users according to the tools' issue tracker and they have not been fixed by developers.

Answer to RQ3: Existing tools detect at most 6.04% of vulnerabilities in  $\mathbb{B}^A$ , suggesting their weaknesses in exposing front-running vulnerabilities in real-world contracts. Effective detection tools are urgently needed.

#### D. Discussion on Limitations of Existing Techniques

We randomly sample FN attacks for each tool with 95% confidence level and 5% confidence interval and manually analyze them to understand the reasons behind the poor performance of existing techniques. We focus only on those FN attacks whose concerned contracts can all be successfully analyzed by the tool since we aim to investigate limitations of each tool's technique rather than its implementation. The large second column of Table III shows the number of sampled attacks. The results indicate that existing techniques are suffering from limitations in their code analysis process and vulnerability detection oracles. The number of attacks whose vulnerabilities are missed due to four identified limitations of the technique of each tool is shown in the large third column of Table III.

TABLE IV  
THE NUMBER OF ATTACKS IN WHICH EACH TYPE OF VICTIM'S FINANCIAL PROFITS DECREASES.

	Ether	ERC20	ERC721	ERC777	ERC1155
Attacks in $\mathbb{D}^A$	118,702	184,987	2,931	1,060	537

1) *Two Limitations in Code Analysis:* We find that existing techniques lack support for inter-contract analysis of the scenarios where a contract invokes another contract during its execution. Existing techniques are designed to analyze contracts individually, while ignoring their possible interactions with other contracts. For example, the vulnerability in Fig 2 cannot be detected if each contract is individually analyzed because the vulnerable exchange rate computation (line 8) and the loading of attack altered data reside in different contracts. The influence traces of 222 (57.96%) attacks in  $\mathbb{D}^S$  span across multiple contracts, indicating that inter-contract analysis is essential to the detection of many vulnerabilities.

Another limitation in code analysis is the unavailability of efficient constraint solvers for cryptographic operations. The path condition at line 3 in Fig 1 involves digital signature verification. It is impossible for techniques like that of Ethracer to resolve a valid input to satisfy this path condition using existing SMT solvers. Hash operations are also widely used in smart contracts to compute the address of values in mapping or array variables. Using such variables may also make constraints unsolvable in symbolic execution. Other symbolic execution-based techniques do not suffer from this limitation, since they do not need to generate concrete function inputs. Their workaround for cryptographic operations is to use new intermediate variables to represent the operation results.

2) *Two Limitations in Oracle:* Each technique defines specific patterns to identify vulnerabilities in smart contracts. Oyente computes the number of digital assets transferred with symbolic execution. Oyente reports front-running vulnerabilities if there exist two execution paths transferring in different symbolic amounts. Vulnerabilities like that in Fig 2 are missed, since the victim's profits are symbolically unchanged. Mythril and Conkas identify vulnerabilities by checking if the receiver or amount of digital asset transfers depends on shared variables modifiable by other transactions. However, some path condition alteration attacks like Fig. 1 may be missed since the profit transfer control-depends, instead of data-depends, on the attack altered data. Ethracer does not consider failed victim transactions as attack consequences. Many vulnerabilities like Fig. 1 are missed. Securify, Securify2, and Sailfish use a general pattern, checking whether digital asset transfers depend on blockchain shared data through either control flow or data flow. However, according to the previous study [14], false alarms are likely to be induced, since such dependency may not result in financial loss of victim.

In addition to detection patterns, the negligence of profit making in tokens by existing techniques causes many attacks undetected. All techniques except that of Ethracer support only Ether as digital assets in pattern matching of vulnerability

detection. Vulnerabilities like Fig 1 and Fig 2 are missed, since the techniques are unaware of the attack profits in tokens. Tokens are even more prevalent than Ether in the dataset presented in Section IV-C. Table IV shows the number of attacks in which different types of tokens are involved. The support of profit analysis in tokens is essential to the vulnerability detection for smart contracts.

## VII. THREATS TO VALIDITY

A validity threat in our study is that our analysis is based on the attacks in 800,000 blocks instead of the entire blockchain history. We mitigate this threat by using the latest blocks to improve the representativeness of the attacks in our benchmark. We also focus on 1200 popularly attacked contracts, as discussed in Section V-D, and show that most exploited vulnerabilities in these contracts have been identified in our benchmark. In addition, we may execute existing contract analyzers improperly. We mitigate this threat by strictly following the instructions and actively communicating with the tool authors when encountering issues. Another validity threat arises from the subjectivity in manual analysis when evaluating our search algorithm and influence trace. We mitigate this threat by reaching a consensus among independent manual checks from three different authors.

## VIII. CONCLUSION

In this paper, we design an algorithm to automatically search for real-world front-running attacks. We localize vulnerable contract code using dynamic taint analysis on the found attacks and build a benchmark of front-running vulnerabilities. Based on the benchmark, we perform an empirical evaluation of seven state-of-the-art vulnerability detection techniques. We find that the performance of these techniques is still limited and identify four limitations in their code analysis process and vulnerability detection oracles.

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