

FlashSyn: Flash Loan Attack Synthesis via Counter Example Driven Approximation (Extended Version)

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ABSTRACT

In decentralized finance (DeFi), lenders can offer flash loans to borrowers, i.e., loans that are only valid within a blockchain transaction and must be repaid with fees by the end of that transaction. Unlike normal loans, flash loans allow borrowers to borrow large assets without upfront collaterals deposits. Malicious adversaries use flash loans to gather large assets to exploit vulnerable DeFi protocols.

In this paper, we introduce a new framework for automated synthesis of adversarial transactions that exploit DeFi protocols using flash loans. To bypass the complexity of a DeFi protocol, we propose a new technique to approximate the DeFi protocol functional behaviors using numerical methods (polynomial linear regression and nearest-neighbor interpolation). We then construct an optimization query using the approximated functions of the DeFi protocol to find an adversarial attack constituted of a sequence of functions invocations with optimal parameters that gives the maximum profit. To improve the accuracy of the approximation, we propose a novel counterexample driven approximation refinement technique. We implement our framework in a tool named FlashSyn.

We evaluate FlashSyn on 16 DeFi protocols that were victims to flash loan attacks and 2 DeFi protocols from Damn Vulnerable DeFi challenges. FlashSyn automatically synthesizes an adversarial attack for 16 of the 18 benchmarks. Among the 16 successful cases, FlashSyn identifies attack vectors yielding higher profits than those employed by historical hackers in 3 cases, and also discovers multiple distinct attack vectors in 10 cases, demonstrating its effectiveness in finding possible flash loan attacks.

CCS CONCEPTS

• Security and privacy → Software security engineering; • Software and its engineering → Software testing and debugging.

KEYWORDS

program synthesis, program analysis, blockchain, smart contracts, vulnerability detection, flash loan

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1 INTRODUCTION

Blockchain technology enables the creation of decentralized, resilient, and programmable ledgers on a global scale. Smart contracts, which can be deployed onto a blockchain, allow developers to encode intricate transaction rules that govern the ledger. These features have made blockchains and smart contracts essential infrastructure for a variety of decentralized financial services (DeFi). As of April 1st, 2023, the Total Value Locked (TVL) in 1,417 DeFi smart contracts had reached 50.15 billion [22].

However, security attacks are critical threats to smart contracts. Attackers can exploit vulnerabilities in smart contracts by sending malicious transactions, potentially stealing millions of dollars from users. Particularly, a new type of security threat has emerged, exploiting design flaws in DeFi contracts by leveraging large amounts of digital assets. These attacks, commonly referred to as *flash loan attacks* [55, 69, 85], typically involve borrowing the required large amount of assets from flash loan contracts. Among the top 200 costliest attacks recorded in Rekt Database, the financial loss caused by 36 flash loan attacks exceeds 418 million USD [55].

A typical flash loan attack transaction consists of a sequence of actions, or function calls to smart contracts. The first action involves borrowing a substantial amount of digital assets from a flash loan contract, while the last action returns these borrowed assets. The sequence of actions in the middle interacts with multiple DeFi contracts, using the borrowed assets to exploit their design flaws. When a DeFi contract fails to consider corner cases created by the large volume of the borrowed assets, the attacker may extract prohibitive profits. For example, many flash loan attacks use borrowed assets to temporarily manipulate asset prices in a DeFi contract to trick the contract to make unfavorable trades with the attacker [13, 60]. Although researchers have developed many automated program analysis and verification techniques [3, 36, 46, 57] to detect and eliminate bugs in smart contracts, these techniques cannot handle flash loan attack vulnerabilities. This is because such vulnerabilities are design flaws rather than implementation bugs. Moreover, these techniques typically operate with one contract at a time, but flash loan attacks almost always involve multiple DeFi contracts interacting with each other.

FlashSyn: We present FlashSyn, the first automated end-to-end program synthesis tool for detecting flash loan attack vulnerabilities. Given a set of smart contracts and candidate actions in these

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contracts, FlashSyn automatically synthesizes an action sequence along with all action parameters to interact with the contracts to exploit potential flash loan vulnerabilities. Additionally, FlashSyn can analyze past blockchain transaction history, assisting users in identifying candidate actions for synthesis.

The primary challenge FlashSyn faces is that the underlying logic of DeFi actions is often too sophisticated for standard solvers to handle. Even if the action sequence was already known, a naive application of symbolic execution might not be able to find action parameters because it may need to extract overly complicated symbolic constraints causing the solvers to time out. Moreover, FlashSyn synthesizes the action sequence and the action parameters together and therefore faces an additional search space explosion challenge.

FlashSyn addresses these challenges with its novel *synthesis-via-approximation* technique. Instead of attempting to extract accurate symbolic expressions from smart contract code, FlashSyn collects data points to approximate the effect of contract functions with numerical methods. FlashSyn then uses the approximated expressions to drive the synthesis. FlashSyn also incrementally improves the approximation with its novel *counterexample driven approximation refinement* techniques, i.e., if the synthesis fails because of a large deviation caused by the approximations, FlashSyn collects the corresponding data points as counterexamples to iteratively refine the approximations. The combination of these techniques allows the underlying optimizer of FlashSyn to work with more tractable expressions. It also decouples the two difficult tasks, finding the action sequence and finding the action parameters. When working with a set of coarse-grained approximated expressions, FlashSyn can filter out unproductive action sequences with a small cost.

Experimental Results: We evaluate FlashSyn on 16 DeFi benchmark protocols that were victims to flash loan attacks and 2 DeFi benchmark protocols from Damn Vulnerable DeFi challenges [19]. FlashSyn synthesizes adversarial attacks for 16 out of the 18 benchmarks. For comparison, a baseline with manually crafted accurate action summaries only synthesizes attacks for 7 out of the 18.

Contributions: This paper makes the following contributions:

- **FlashSyn:** The first automated end-to-end program synthesis tool for detecting flash loan attack vulnerabilities. It enables approximate attack synthesis without diving into sophisticated logics of DeFi contracts.
- **Synthesis-via-approximation:** A novel synthesis-via-approximation technique to handle sophisticated logics of DeFi contracts.
- **Counterexample Driven Approximation Refinement:** A novel counterexample driven approximation refinement technique to incrementally improve the approximation during the synthesis process.
- **Experimental Evaluation:** We implemented FlashSyn in a tool and evaluated it on 16 protocols that were victims to flash loan attacks and 2 fictional flash loan attacks.

Our solution, FlashSyn has been adopted and further developed by Quantstamp, a leading smart contract auditing company for the detection of flash loan vulnerabilities in DeFi contracts [54, 61, 62].

2 BACKGROUND

Blockchain: Blockchain is a distributed ledger that broadcasts and stores information of transactions across different parties. A

blockchain consists of a growing number of blocks and a consensus algorithm determining block order. Each block is constituted of transactions. Ethereum [12, 80] is the first blockchain to support, store, and execute Turing complete programs, known as smart contracts. Many new blockchains use the Ethereum virtual machine (EVM) for execution due to its popularity among developers.

Smart Contracts: Each smart contract is associated with a unique address, a persistent account’s storage trie, a balance of native tokens, e.g., Ether in Ethereum, and bytecode (e.g., EVM bytecode [12, 80]) that executes incoming transactions to change the storage and balance. Users interact with a smart contract by issuing transactions from their user accounts to the contract address. Smart contracts can also interact with other smart contracts as function calls. Currently, there are several human-readable high-level programming languages, e.g., Solidity [38] and Vyper [39], to write smart contracts that compile to the EVM bytecode.

Decentralized Finance (DeFi): DeFi is a peer-to-peer financial ecosystem built on top of blockchains [81]. The building blocks of DeFi are smart contracts that manage digital assets. A few DeFi protocols dominate the DeFi market and serve as references for other decentralized applications: stable coins (e.g., USDC and USDT), price oracles, decentralized exchanges, and lending and borrowing platforms. In DeFi, a special type of loan called **flash loan** allows lenders to offer loans to borrowers without upfront collateral deposits. The loan is only valid within a single transaction and must be repaid with fees before the completion of the transaction.

3 ILLUSTRATIVE EXAMPLE

We next present a motivating example to describe the complexity of flash loan attacks and our proposed approach to synthesize them.

Background: On October 26th 2020, an attacker exploited the USDC and USDT vaults of Harvest Finance, causing a financial loss of about 33.8 million USD. In this section, we will focus on the attack on the USDC vault. The attacker repeatedly executed the same attack vector 17 times targeting the USDC vault. Fig. 1 summarizes the attack vector. The attack vector contains a sequence of actions that interact with the following contracts:

- **Uniswap:** Uniswap is a protocol with flash loan services.
- **Curve:** Curve is an exchange protocol for stable coins like USDT, USDC, and DAI, whose market prices are close to one USD. It maintains pools of stable coins and users can interact with these pools to exchange one kind of stable coins to another. For example, Y Pool in Curve contains both USDC and USDT. Users can put USDC into the pool to exchange USDT out. The exchange rate fluctuates around one, which is determined by the current ratio of USDC and USDT in the pool. Note that internally Y pool automatically deposits USDT and USDC to *Yearn*¹, keeps yUSDT and yUSDC tokens, and retrieves them back when the users withdraw. We omit this complication for simplicity.
- **Harvest:** Harvest is an asset management protocol and the victim contract of this attack. Users can deposit USDC and USDT into Harvest and receive fUSDC and fUSDT tokens which users can later use to retrieve their deposit back. Harvest will invest the deposited USDC and USDT from users to other DeFi protocols to

¹Yearn is a DeFi protocol that generates yield on deposited assets. yTokens of Yearn represent the liquidity provided in a Yearn product.

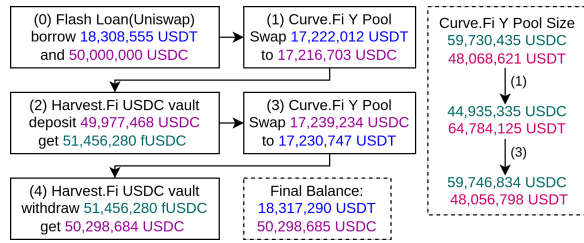


Figure 1: Harvest USDC Vault Price Manipulation Attack.

generate profit. Note that the exchange rate between fUSDC and USDC is also not fixed. It is determined by a vulnerable closed source oracle contract, which ultimately uses Curve Y pool ratios to calculate the exchange rate.

Attack Actions: The attack vector shown in Fig. 1 first flash loaned 18.3M USDT and 50M USDC, then called 4 methods (actions) to exploit the design flaw in Harvest. The first action, action 1, swaps 17, 222, 012 USDT for 17, 216, 703 USDC via *Curve.Fi Y Pool*. Action 1 reduces the estimated value of USDT based on the ratio in Y pool as the amounts of USDT in Y Pool considerably increases. This in turn reduces Harvest Finance’s evaluation of its invested assets. Action 2 deposits 49, 977, 468 USDC into *Harvest Finance USDC vault* and due to the reduced evaluation of the invested underlying assets, the attacker receives 51, 456, 280 fUSDC back, which is abnormally large. Similar to action 1, action 3 then swaps 17, 239, 234 USDC back to 17, 230, 747 USDT via *Curve.Fi Y Pool*, which normalized the manipulated USDT/USDC rate in the pool. It also brings Harvest Finance’s evaluation of its invested underlying asset back to normal. Finally, action 4 withdraws 50, 298, 684 USDC (using 51, 456, 280 fUSDC) from *Harvest Finance USDC vault*. Assuming 1 USDC = 1 USDT = 1 USD, the profit of the above attack vector is 307, 420 USD.

This attack is a typical case of oracle manipulation. The exploiter manipulated the USDT/USDC rate in *Curve.Fi Y Pool* by swapping a large amount between USDC and USDT back and forth, which caused Harvest Finance protocol to incorrectly evaluate the value of its asset, leaving large arbitrage space for the exploiter. The actions sequence and particularly the parameters are carefully chosen by the attacker to yield best profit. There are multiple challenges FlashSyn faces to synthesize this attack.

Challenge 1 - Sophisticated Interactions: The attack involves several smart contracts that interact with each other and with other contracts outside the attack vector. The state changes caused by one action influence the behavior of other actions. This makes the synthesis problem of finding an attack vector more complicated as the effect of an action depends on its predecessor actions thus actions cannot be treated separately.

Challenge 2 - Close Source: Some external smart contracts that a DeFi protocol interacts with are not *open-source*. For instance, the source code of the external smart contract *PriceConverter*² of Harvest Finance protocol is not available on Etherscan [34], and it is called by actions 2 and 4 to determine the exchange rate between fUSDC and USDC. This impedes the complete understanding of the DeFi protocol implementation and to reason about its correctness to anticipate attacks vectors.

²Ethereum address: 0xfca4416d9def20ac5b6da8b8322b659770efbf.

```

1 function get_D(uint[] xp) returns (uint):
2   uint N_COINS = xp.length;
3   uint S = sum(xp);
4   // ...
5   uint D = S;
6   uint Ann = A * N_COINS; // A is a constant
7   for (uint i = 0; i < 255; i = i + 1) {
8     uint D_P = D;
9     for (uint j = 0; j < xp.length; j = j + 1) {
10      D_P = (D_P * D) / (xp[j] * N_COINS + 1);
11    }
12    uint Dprev = D;
13    D = ((Ann * S + D_P * N_COINS) * D) /
14      ((Ann - 1) * D + (N_COINS + 1) * D_P);
15    if (abs(D - Dprev) <= 1) break;
16  }
17  return D;

```

Figure 2: *get_D* Method to Compute *D*.

Challenge 3 - Mathematical Complexity: DeFi contracts use mathematical models that are too complex to reason about. For instance, actions 2 and 4 swap an amount of token *i* to token *j*, while maintaining the following *StableSwap invariant* [23]:

$$A \cdot n^n \sum_i x_i + D = A \cdot n^n \cdot D + \frac{D^{n+1}}{n^n \prod_i x_i}$$

where *A* is a constant, *n* is number of token types in the pool (4 for *Curve.Fi Y Pool*)³, *x_i* is token *i*’s liquidity, *D* is the total amount of tokens at equal prices. There does not exist a closed-form solution for *D* as it requires finding roots of a *quintic equation*. In the actual implementation, *D* is calculated iteratively on the fly via Newton’s method (see Appendix A).

To demonstrate the complexity of DeFi protocols, we run an experiment with Manticore [57], a symbolic execution tool for smart contracts, to execute the function *get_D*, for computing *D* as shown in Fig. 2, with symbolic inputs and explore all possible reachable states. Manticore fails and throws a solver-related exception together with an *out of memory* error. We then simplified *get_D* by removing the outer *for* loop and bounding the length of *xp* to 2, Manticore still fails and throws the same error.

3.1 Apply FlashSyn

We will now show how FlashSyn synthesizes the Harvest USDC vault attack from the identified set of actions listed in Table 1.⁴ The first two input arguments to *exchange* specify the token types to be swapped. The third argument specifies the quantity to swap.⁵ Table 1 lists each action’s token flow, along with the number of data points collected initially (without counterexamples) and the total number of data points for polynomial and interpolation, respectively. The amounts of tokens transferred in/out for each action are calculated based on its contract’s member variables or read-only functions. We refer these variables and functions as **states** of an action. A **prestate** refers to the state before the execution of an action. Executing an action will also alter states, which are denoted as **poststates**. The states not altered by any action are ignored.

³Ethereum address: 0x45f783cce6b7ff23b2ab2d70e416cbb7d6055f51.

⁴In Section 6, we present FlashFind to automatically find the set of candidate actions that are used here by FlashSyn to synthesize an attack vector.

⁵Note that in the implementation the actual name of the *exchange* method is *exchange_underlying*, 1 and 2 are used to identify the tokens USDC and USDT, respectively, and the method has a fourth argument to specify the minimal quantity expected to receive from the swapping.

Table 1: Actions in Harvest USDC Vault Attack. IDP and TDP denotes the initial and total number of datapoints. USDT(-) (resp., USDC(+)) denotes USDT (resp., USDC) tokens transferred out (reps., in).

Action	Token Flow	IDP	TDP-Poly	TDP-Inter
exchange (USDT, USDC, v)	USDT(-), USDC(+)	2000	2238	2792
exchange (USDC, USDT, v)	USDC(-), USDT(+)	2000	2148	2888
deposit(v)	USDC(-), fUSDC(+)	2000	2162	2358
withdraw(v)	fUSDC(-), USDC(+)	2000	2364	2876

For example, `exchange(USDT, USDC, v)` leverages two states, `balances[USDC]` and `balances[USDT]`, to calculate the amounts of token exchanges. Upon execution, this function also modifies these two states. Consequently, these two states act as both the prestates and poststates of `exchange(USDT, USDC, v)`.

Initial Approximation: To generate the initial approximation of the state transition functions of each action, FlashSyn first collects data points where each data point is an *input-output* pair. The *input* is the action’s prestates and parameters, and the *output* is its poststates and the outputted values. To collect data points, FlashSyn executes the associated contracts on a private blockchain (a forked blockchain environment) with different parameters to reach *input-output* pairs with different prestates and poststates. FlashSyn then uses the collected data points to find the approximated state transition functions. We consider two techniques to solve the above multivariate approximation problem: linear regression based polynomial features and nearest-neighbor interpolation [56, 65]. The following example is one of `exchange(USDT, USDC, v)`’s state transition functions approximated by polynomials: $s'_1 = 0.73244455 \times s_1 - 0.23655202 \times s_2 - 0.85915531 \times v + 27351279.416023515$ where s_1 and s'_1 are the prestate and poststate `balances[USDC]`, s_2 is the prestate `balances[USDT]`, and v is the third argument of the action `exchange(USDT, USDC, v)`.

Enumerate and Filter Action Sequences: After capturing an initial approximation of state transition functions, FlashSyn leverages an enumeration-based top-down algorithm to synthesize different action sequences. FlashSyn applies several pruning heuristics to filter unpromising sequences. For each enumerated action sequence, FlashSyn uses the approximated state transition functions to construct an optimization problem, consisting of constraints and an objective function that represents profit. FlashSyn then applies an off-the-shelf optimizer to obtain a list of parameters that maximize the profit estimated using approximated transition functions.

Counterexample Driven Refinement: After obtaining a list of parameters that maximize the estimated profit of an action sequence, FlashSyn proceeds to verify the synthesized attack vectors by executing them on a private blockchain and check their actual profits. If the difference between the actual profit and the estimated profit of an attack vector is greater than 5%, FlashSyn reports it as a counterexample, indicating inaccuracy of our approximated transition functions. To correct this inaccuracy, FlashSyn employs *counterexample driven approximation refinement* technique. FlashSyn utilizes the reported counterexamples to collect new data points and refine the approximations. The revised approximations are subsequently used to search for

parameters in next loops. For example, FlashSyn with polynomial approximations collects 238 additional data points for the action `exchange(USDT, USDC, v)` throughout 7 refinement loops.

Synthesized Attack: In the Harvest USDC example, FlashSyn successfully found the following attack vector that yields an adjusted profit of 110051 USD using the interpolation technique with the counterexample driven refinement loop.

$$\text{exchange}(\text{USDT}, \text{USDC}, 15192122) \cdot \text{deposit}(45105321) \cdot \text{exchange}(\text{USDC}, \text{USDT}, 11995404) \cdot \text{withdraw}(46198643)$$

4 PRELIMINARY

Labeled Transition Systems (LTS). We use LTS to model behaviors of smart contracts. A LTS $A = (Q, \Sigma, q_0, \delta)$ over the possibly-infinite alphabet Σ is a possibly-infinite set Q of states with an initial state $q_0 \in Q$, and a transition relation $\delta \subseteq Q \times \Sigma \times Q$.

Execution. An *execution* of A is a sequence of states and transition labels (*actions*) $\rho = q_0, a_0, q_1 \dots a_{k-1}, q_k$ for $k > 0$ such that $\delta(q_i, a_i, q_{i+1})$ for each $0 \leq i < k$. We write $q_i \xrightarrow{a_i \dots a_{j-1}}_A q_j$ to denote the subsequence $q_i, a_i, \dots, q_{j-1}, a_{j-1}, q_j$ of ρ .

Invocation Label. Formally, an *invocation label* $\text{adr}.m(\vec{u})$ consists of a method name m of a contract address adr , accompanied by a vector \vec{u} containing argument values.

Operation Label. An *operation label* $\ell := \text{adr}.m(\vec{u}) \Rightarrow (I, v) \cup \perp$ is an invocation label $\text{adr}.m(\vec{u})$ along with a return value v , and I is a sequence of operation labels representing the “internal” calls made during the invocation of m . The distinguished invocation outcome \perp is associated to invocations that revert.

Interface. The *interface* Σ_{adr} is the set of non-read-only operation labels in the contract adr . We assume w.l.o.g. that the preconditions are satisfied for all the operations in Σ_{adr} , otherwise, the external invocation $\text{adr}.m(\vec{u})$ reverts. Σ_{adr} is a superset of the set of action candidates of FlashSyn.

Smart Contract. A *smart contract* at an address adr is an LTS $C_{\text{adr}} = (Q_{\text{adr}}, \Sigma_{\text{adr}}, q_0, \delta_{\text{adr}})$ over the interface Σ_{adr} where Q_{adr} is the set states and δ_{adr} is the transition relation.

Symbolic Actions Vector. We define the notion of a symbolic actions vector $S = \ell_{\text{adr}1} \dots \ell_{\text{adr}n}$ s.t. $\ell_{\text{adr}i} \in \Sigma$ for $1 \leq i < n$ as the sequence of operation labels (possibly from different contracts) associated with the execution ρ , i.e., $\rho = q_1, \ell_{\text{adr}1}, q_1 \dots \ell_{\text{adr}n}, q_n$.

Balance. We define the balance of address adr in a blockchain state q as the mapping $\mathcal{B} : Q \times \mathbf{A} \Rightarrow \mathbf{V}$ that maps the pair $(q, \text{adr}) \in Q \times \mathbf{A}$ to the weighted sum of tokens the address adr holds at q , i.e., $\mathcal{B}(q, \text{adr}) = \sum_{t \in \mathbf{T}} \mathbf{M}(q, \text{adr}, t) \cdot \mathbf{P}(t)$, where \mathbf{T} represents tokens hold by adr , $\mathbf{M}(q, \text{adr}, t)$ represents the amount of token t hold by adr at the blockchain state q , and $\mathbf{P}(q, t)$ represents the price of token t at the blockchain state q .

Attack Vector. An *attack vector* by an adversary adr consists of a symbolic actions vector S where the symbolic arguments are replaced by concrete values (integer values) and S transforms a blockchain state q to another state q' such that $\mathcal{B}(q', \text{adr}) - \mathcal{B}(q, \text{adr}) > 0$, i.e., the adversary adr generates profit when the sequence of actions S is executed with the concrete values.

Problem formulation. Given a specification φ (which contains vulnerable contract addresses or action candidates) and a blockchain state q , the objective is to find an attack vector consisting of a concretization of the symbolic actions vector

$S = \ell_{adr1} \dots \ell_{adrn}$ s.t. $\ell_{adri} \in \Sigma \cap \varphi$ for $1 \leq i < n$, transforming the state q to a state q' , and that maximizes the profit of an adversary adr , $\mathcal{B}(q', adr) - \mathcal{B}(q, adr)$.

5 FLASHSYN

5.1 Symbolic Actions Vectors Synthesis

Algorithm 1 gives the overall synthesis procedure of FlashSyn. FlashSyn first collects initial data points to approximate the actions in \mathbf{Act} (line 3) where FlashSyn uses the state q as a starting blockchain state. Then, using the sub-procedure APPROXIMATE FlashSyn generates the approximations ApproxAct of the actions in \mathbf{Act} using the collected data points (line 5). FlashSyn uses the sub-procedure ACTIONSVECTORS to generate all possible symbolic actions vectors of length less than len (line 6). FlashSyn then iterates over the generated actions vectors and uses some heuristics implemented in the sub-procedure ISFEASIBLE to prune actions vectors (line 8). For instance, an actions vector containing two adjacent actions invoking the same method can be pruned to an actions vector where the two adjacent actions are merged. Afterwards, using the actions vector and approximated transition functions, the sub-procedure CONSTRUCT constructs the optimization framework \mathcal{P} for the actions vector (line 9). Then, FlashSyn uses the optimization sub-procedure OPTIMIZE (line 10) to find the optimal concrete values to pass as input parameters to the methods in the actions vector that satisfy the constraints of \mathcal{P} . FlashSyn then validate whether the attack vector generated by the optimizer indeed generates the profit with the sub-procedure QUERYORACLE to execute the generated attack vectors on the blockchain. If the query is successful, i.e., the actual profit closely matches the profit found by the optimizer, FlashSyn adds the attack vector to the list of discovered attacks. Otherwise, FlashSyn considers the attack vector to be a counterexample, and uses it to generate new data points to refine the approximation in the subsequent iterations, within the sub-procedure CEGDC (referenced in line 14 and introduced later in Section 5.4). FlashSyn repeats the process until the number of iterations reaches n (line 4).

Algorithm 1: Attack vectors synthesis procedure. Its inputs are actions \mathbf{Act} , the maximum length len , a blockchain state q , and a threshold number of iterations n . Its outputs are attack vectors that yield positive profits.

```

1: procedure SYNTHESIZE( $\mathbf{Act}$ ,  $len$ ,  $P$ ,  $q$ ,  $n$ )
2:   for each  $a \in \mathbf{Act}$ 
3:     datapoints[ $a$ ]  $\leftarrow$  DATACOLLECT( $q$ ,  $a$ );
4:   for each  $i \in [0; n]$ 
5:     ApproxAct  $\leftarrow$  APPROXIMATE( $\mathbf{Act}$ , datapoints);
6:     wlist  $\leftarrow$  ACTIONSVECTORS(ApproxAct,  $len$ );
7:     for each  $p \in wlist$ 
8:       if ISFEASIBLE( $p$ )
9:          $\mathcal{P} \leftarrow$  CONSTRUCT( $p$ , ApproxAct)
10:        ( $p^*$ , profit)  $\leftarrow$  OPTIMIZE( $p$ ,  $\mathcal{P}$ );
11:        if QUERYORACLE( $q$ ,  $p^*$ , profit)
12:          answerlist.add( $p^*$ , profit);
13:        else
14:          datapoints := datapoints  $\cup$  CEGDC( $p^*$ ,  $q$ );
15:   return answerlist;
```

5.2 Pruning Symbolic Actions Vectors

The sub-procedure ISFEASIBLE implements some heuristics to prune undesired symbolic actions vectors.

Heuristic 1: no duplicate adjacent actions. Two successive calls to the same method in a DeFi smart contract are usually equivalent to a single call with larger parameters. Thus, we discard actions vectors containing duplicate, successive actions.

Heuristic 2: limited usage of a single action. Using the observation that attack vectors do not contain repetitions, we fix a maximum number of calls to a single method an attack can contain and discard actions vectors that do not satisfy this criterion, e.g., an actions vector of length 4 cannot contain more than 2 calls to the same method.

Heuristic 3: necessary preconditions. Based on the observation that owning certain tokens is a necessary precondition for invoking some actions, FlashSyn prunes symbolic actions vectors that contain actions requiring tokens⁶ not owned by the attacker. For example, in Harvest USDC example, invoking *withdraw* method requires users own some share tokens (fUSDC) beforehand. The only action candidate that mints fUSDC for users is *deposit*; thus, this heuristic mandates that *deposit* must be called before invoking *withdraw*. This heuristic establishes a necessary but not sufficient condition to ensure that synthesized attack vectors will not be reverted.

5.3 Optimization

Given a symbolic actions vector and their approximated transit functions, the sub-procedure CONSTRUCT constructs an optimization framework to find optimal values for the parameters for the actions. Recall that given a blockchain state q and an address adr , the actions vector S transforms q to another state q' . The objective function in the optimization problem targets to increase the tokens values in the balance of the address adr , i.e., $y = \mathcal{B}(q', adr) - \mathcal{B}(q, adr)$. The optimization problem is accompanied by constraints on the symbolic values to be inferred. For instance, the balance of any token t for any address adr' must always be non-negative, i.e., the adversary and the smart contracts cannot use more tokens than what they have in their balances, otherwise the transaction reverts. In the following, we give the definition of the optimization problem.

$$\mathcal{P} : \begin{cases} \max_{p_0, p_1, \dots, p_n} y = \mathcal{B}(q', adr) - \mathcal{B}(q, adr) \\ \text{subject to: } \forall t \in T, adr' \in A. M(q', adr', t) \geq 0 \end{cases}$$

5.4 Counterexample Guided Data Collection (CEGDC)

The optimization sub-procedure might explore parts of the states space not explored during the initial data points collection. This might challenge the accuracy of the approximations and result in mismatch between the estimated and the actual values. Thus, it is necessary to collect new data points based on the counterexamples that show the mismatch between the estimated and the actual values, to refine the approximations. Therefore, we propose counterexample guided data collection (CEGDC),

⁶Note a token can be standard tokens (ERC20, BEP20), or any other forms of tokens such as debt tokens or share tokens.

inspired of counterexample guided abstraction refinement [17], to refine approximations when mismatches are identified.

We use C to denote the attack vector s.t. $q \xrightarrow{C} q'$. q'_e and q'_a denote the estimated value for the state q' found by the optimizer and the actual value obtained when executing C on the actual protocol on the blockchain, respectively. $\mathcal{P}_e(C) = \mathcal{B}(q'_e, \text{adr}) - \mathcal{B}(q, \text{adr})$ and $\mathcal{P}_a(C) = \mathcal{B}(q'_a, \text{adr}) - \mathcal{B}(q, \text{adr})$ denote the estimated profit and actual profit, respectively.

DEFINITION 5.1. *A counterexample is an attack vector C whose estimated profit $\mathcal{P}_e(C)$ is different from its actual profit $\mathcal{P}_a(C)$. Formally, $|\mathcal{P}_e(C) - \mathcal{P}_a(C)| \geq \varepsilon \cdot (|\mathcal{P}_e(C)| + |\mathcal{P}_a(C)|)$, where ε is a small constant representing accuracy tolerance.*

Algorithm 2: Counterexample guided data collection procedure. It takes a counterexample C and a state q , and returns datapoints. $k \in [n; 1]$ means that in the first iteration $k = n > 0$.

```

1: procedure CEGDC( $C, q$ )
2:   datapoints  $\leftarrow$  [ ];
3:   for each  $k \in [len(C); 1]$ ;
4:      $q'_e \leftarrow$  ESTIMATE( $q, C, k$ );
5:      $q'_a \leftarrow$  EXECUTE( $q, C, k$ );
6:     if ISACCURATE( $q'_e, q'_a$ )
7:       returns datapoints ;
8:     else
9:       ( $a, paras$ )  $\leftarrow$  C[ $k$ ];
10:      datapoints[ $a$ ]  $\leftarrow$  ( $q, paras, q'_a$ );
11:   return datapoints;
```

In Algorithm 2, we present the sub-procedure CEGDC for collecting new data points from a counterexample. CEGDC takes as inputs a counterexample C which is known to have an inaccurate profit estimation, and a blockchain state. The for loop on line 3 is used to locate approximation errors backward from the last action to the first action and collect new data points accordingly. In a loop iteration k , FlashSyn checks if the estimated methods of the action at the index k of C are accurate. First, FlashSyn computes the estimated state q'_e reached by executing C until reaching the action indexed k (line 4) using the approximated transition functions. Second, FlashSyn fetches the actual state q'_a reached by executing C until reaching the action indexed k (line 5) on the actual smart contracts on the blockchain. Then, FlashSyn compares the estimated and actual execution results (line 6). If the estimation is accurate, this indicates that the transition functions of the action at the index k of C and its predecessors are accurate; so the procedure breaks the loop and returns the data points computed in the previous iterations (line 7). Otherwise, it indicates inaccurate transition functions of this action or/and its predecessors. Thus, we add a new data point associated with the action at the index k of C (lines 9 and 10) and proceed to the next iteration of the loop to explore the action predecessors.

5.5 FlashFind: Action Candidates Identification

Flash loan attacks typically focus on victim contracts containing functions capable of transferring tokens,⁷ which can be invoked by regular users. The attacker manipulates the transfer amount under specific conditions to make profit.

⁷Here, tokens refer to various forms of DeFi tokens, including stable coins, debt tokens, share tokens, liquidity tokens, asset tokens, etc.

We designed and built a tool FlashFind to assist users of FlashSyn to select action candidates likely to be involved in an attack vector. Given a set of target smart contracts, FlashFind identifies action candidates in the following steps.

5.5.1 Selecting Action Candidates from Contract Application Binary Interfaces (ABIs). For all verified smart contracts, their ABIs are made public to facilitate users to call functions and engage with the contracts. An ABI typically comprises (public or external) function names, argument names/types, function state mutability, and return types. During the process of selecting action candidates, certain functions can be safely ignored: (1) Functions with the view or pure mutability can be excluded. (2) Functions that can only be invoked by privileged users, such as *transferOwnership* and *changeAdmin*, can also be disregarded since they are unlikely to be accessed by regular users⁸. (3) Token permission management functions/parameters, such as the function *approve* or parameter *deadline*, are excluded⁹. These functions/parameters solely control whether a transaction will be reverted or not and do not affect the behaviors of contracts.

5.5.2 Learning Special Parameters from Transaction History. After selecting a set of action candidates from contracts' ABIs, some non-integer parameters (eg. bytes, string, address, array, enum) can still be unknown. FlashFind collects past transactions of the target contracts and extracts function level trace data from these transactions, and utilizes the trace data to learn the special parameters from previous function calls made to the contract.

5.5.3 Local Execution and Intra-dependency Analysis. After learning special parameters, each action candidate is executed at a given block to verify its executability. An action candidate may not be executable due to various reasons: (1) the function is disabled by the owner or admin; (2) internal function calls to other contracts are disabled by the owners or admins of those contracts; (3) the function is not valid under current blockchain states. The inexecutability due to these reasons cannot be identified by static analysis and can only be determined by executions. All such inexecutable functions are filtered out.

FlashFind automatically collects storage read/write information during the execution of these functions and infers the Read-After-Write (RAW) dependencies¹⁰ between different action candidates. An action A has a RAW dependency (or equivalently, is RAW dependent) on action B if the execution of action A reads the storage written by action B ¹¹. From the RAW dependencies, it is possible to observe that certain functions behave independently, meaning they do not have any RAW dependencies on other functions, and other functions do not have any RAW dependencies on them either. Consequently, these independent functions can be safely ignored.

After analyzing ABIs, transaction history, and local executions, FlashFind generates a list of action candidates with only their

⁸Previous works [45, 51] have extensively researched access control vulnerabilities. We exclude them from the scope of this work.

⁹To simplify the search process of FlashSyn, these permissions are assumed to be granted maximally.

¹⁰This RAW dependency information is also employed in FlashSyn's initial data collection to expand the range of data points.

¹¹It is important to note that this step excludes any tx.origin/msg.sender-related storage reads/writes, as such storage accesses do not alter the global state of the protocol and are therefore unlikely to impact the functional behaviors of actions.

integer arguments left undetermined. These action candidates are then input into FlashSyn for further synthesis.

6 IMPLEMENTATION

FlashSyn is implemented in Python. Figure 3 shows an overview of our implementation. The components *Runner*, *Synthesizer*,

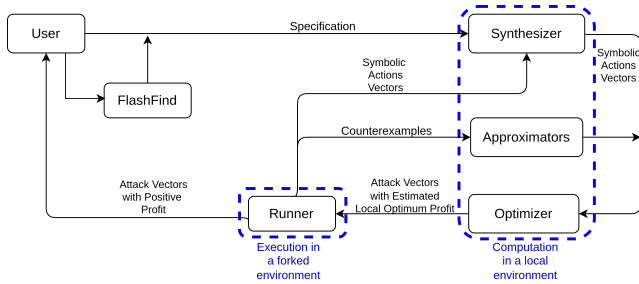


Figure 3: An Overview of FlashSyn Implementation

Approximator, and *Optimizer* implement the FlashSyn synthesis procedure presented in Algorithm 1. An optional component FlashFind is used to automatically identify action candidates.

(1) **Approximator.** *Approximator* approximates the transition functions using data points collected by *Runner*. The approximated transition functions are then given to *Optimizer* to construct the optimization framework. In *Approximator*, all transition functions of an action are approximated unless the transition functions are straightforward assignment/addition/subtraction (by simple inspection of smart contract codes), or the action is very common (such as Uniswap that has been widely studied [60, 82, 84]). FlashSyn implements two numerical methods using external libraries. FlashSyn-poly utilizes sklearn [11, 59], and FlashSyn-inter employs scipy [74]. The choice of polynomial and interpolation methods is motivated by several considerations. First, FlashSyn requires fast evaluation of approximated functions, as thousands of evaluations are performed in the optimization process. Second, when provided with an input not seen before, the approximation method needs to yield a reasonable estimation based on the nearest points. Lastly, given that a typical FlashSyn process involves learning dozens of approximated formulas, the approximation process for one formula should not exceed a few seconds. Polynomial and interpolation methods are the two most popular approximation approaches that meet all of these criteria and there are off-the-shelf tools like sklearn and scipy that are easy to integrate in FlashSyn.

(2) **Optimizer.** *Optimizer* automatically builds an optimization problem using the approximated transition functions returned by *Approximator* and the symbolic actions vectors enumerated by *Synthesizer* and performs global optimization on it. The obtained attack vector that yields a positive profit is then executed by *Runner* to confirm the accuracy of the estimation. If the estimation is inaccurate, the attack vector is treated as a counterexample and is used to collect new data points by *Runner* that are used by *Approximator* to refine the approximation. We built *Optimizer* on top of an off-the-self global optimizer `scipy.optimize.shgo` [24, 48, 75], which solves the simplicial homology global optimization algorithm to find the optimal

parameters.¹² In FlashSyn-poly, we parallelized *Optimizer* component using up to 18 processes where *Optimizer* is run over multiple symbolic actions vectors in parallel.

(3) **Runner.** *Runner* executes transactions on a forked blockchain. It performs both initial and counterexample based data collection, and validates results of *Optimizer*. We implemented *Runner* on top of Foundry [40], a toolkit written in Rust for smart contracts development that allow to interact with EVM based blockchains.

(4) **Synthesizer.** *Synthesizer* first enumerates and prunes symbolic actions vectors using heuristics. Then, during counterexample guided loops, it employs priority scoring to gradually drop actions vectors based on their scores. *Synthesizer* uses iterative synthesis. *Optimizer* can be configured with different hyperparameters to perform different strengths of parameter search. We designed 3 sets of hyperparameters which represent different strengths of parameter search. *Synthesizer* first conducts a weakest parameter search on all enumerated symbolic actions vectors using *Optimizer*. After *Runner* validates the results, *Synthesizer* ranks symbolic actions vectors and drops the ones with low priority scores. The actions vector with high priority score will be searched with higher strengths. Specifically, if a symbolic actions vector yields a positive profit \mathcal{P} in iteration k , its priority score of iteration $k + 1$ is \mathcal{P} . If a symbolic actions vector does not yield a positive profit in iteration k , it is given a small priority score between 1 and 10 based on *Optimizer* results. An actions vector will also be dropped when its priority score does not increase between iterations. When all actions vectors are dropped, the whole synthesis procedure stops, and FlashSyn returns all the profitable attack vectors it found.

(5) **FlashFind.** We also implemented FlashFind as an optional component. FlashFind uses TrueBlocks [66] and Blockchain Explorers (Etherscan [34], BscScan [10], and FtmScan [43]) to collect past transactions of the target contracts. FlashFind employs Phalcon [2] and Foundry [40] to extract function level trace data from those transactions and perform analysis on storage accesses. Our evaluation shows that FlashFind is able to identify action candidates and helps FlashSyn discovers alternative attack vectors (see RQ4 in Section 7).

FlashSyn does not require prior knowledge of a vulnerable location or contract. Given a set of DeFi lego user interface contracts, action candidates and their special parameters such as strings are given by the users or automatically extracted from transaction history using FlashFind. FlashSyn utilizes these action candidates to synthesize attack vectors and search for optimal numerical values. Note that these action candidates are not necessarily the ones that contain the vulnerability. Rather, they serve as user interfaces for interacting with the protocol. The vulnerability may reside in any contract invoked through nested calls originating from these action candidates. If FlashFind is not utilized, users can consult the protocol documentation to identify the appropriate user-interface contracts and functions (action candidates), as well as how to select special parameters for invoking these functions. Such information is essential for

¹²Note that we were not able to use local optimizers in `scipy.optimize` library [74] which require an initial guess of parameters. Under our settings, it is not feasible to find an initial guess for every symbolic attack, as each attack behaves differently.

Table 2: Benchmark of Attacks Used in the Evaluation.

	Benchmark	#C ⁺	LoC [*]	Vulnerability Type	Tx
ETH	bZx1	6	4964	pump&arbitrage	[25]
	Harvest_USDT	6	6446	manipulate oracle	[28]
	Harvest_USDC	6	4095	manipulate oracle	[29]
	Eminence	2	489	design flaw [†]	[27]
	ValueDeFi	8	7043	manipulate oracle	[31]
	Cheesebank	12	1246	manipulate oracle	[26]
	Warp	11	13139	manipulate oracle	[32]
	Yearn	5	2200	forced investment	[33]
BSC	inverseFi	7	5734	manipulate oracle	[30]
	bEarnFi	3	3007	asset mismatch	[6]
	AutoShark	6	8052	design flaw [†]	[5]
	ElevenFi	7	5613	design flaw [†]	[7]
	ApeRocket	7	1562	design flaw [†]	[4]
	WDoge	2	788	deflationary token	[9]
FTM	Novo	4	7080	design flaw [†]	[8]
	OneRing	14	5386	design flaw [†]	[42]
DVD	Puppet	2	742	manipulate oracle	[20]
	PuppetV2	1	161	manipulate oracle	[21]
Total Financial Loss in History				82.5 million USD	

+ : #C denotes number of the victim protocol’s contracts invoked in exploits.

* : LoC denotes total number of lines of code in the contracts identified by #C, excluding closed-source contracts.

† : The logic designs of one or more functions in the victim contracts is flawed, with highly specific case-by-case vulnerabilities.

any user interacting with the protocol, and is generally available in the documentations of DeFi protocols.

7 EVALUATION

We aim to answer the following research questions:

- RQ 1:** How effective is FlashSyn in synthesizing flash loan attack vectors?
- RQ 2:** How well does the synthesis-via-approximation technique perform compared to precise baselines?
- RQ 3:** How much does counterexample driven approximation refinement improve FlashSyn’s results?
- RQ 4:** How effective is the combination of FlashFind and FlashSyn to synthesize attack vectors end-to-end?

Scope: FlashSyn focuses on flash loan attacks that generate positive profit by sequentially invoking functions within existing DeFi contracts. Security attacks that require exploiting other vulnerabilities such as re-entrance or conducting social engineering are outside the scope of FlashSyn and our evaluation. The goal of FlashSyn is to prove the existence and the exploitability of flash loan vulnerabilities. Consequently, activities such as getting and repaying the flash loan are not part of our synthesis task.

Benchmarks: We investigated historical flash loan attacks that span from 02/14/2020 to 06/16/2022 across Ethereum, Binance Smart Chain (BSC), and Fantom (FTM) and attempted to reproduce each of them in our environment. In the end, we reproduced 16 attacks that are within our scope and collected them as our benchmark attacks. These attacks invoked 2-14 contracts of the victim protocol in the nested invocation tree per attack, consisting of a total of 489 to 13,139 lines of code,

reflecting the multifaceted nature of the DeFi protocols exploited in real-world flash loan attacks. Also, protocols in our benchmark contain up to 15 action candidates from which FlashSyn needs to find an attack vector. Altogether, the 16 historical flash loan attacks in our benchmark have caused over 82.5 million US dollars in losses and include widely-known cases such as Harvest, bZx, and Eminence. Additionally, we include 2 fictional attacks from the Damn Vulnerable DeFi (DVD) challenges [19].

Ground Truth: For historical flash loan attacks, we forked the corresponding blockchain at one block prior to the attack transaction and replayed the attacker’s attack vector as the ground truth. For DVD benchmarks, we select community solutions as ground truth. Note that in a flash loan attack, if the same attack vector is repeated multiple times, we remove the loop and only consider the first attack vector as the ground truth.

Precise Baseline: To demonstrate the effectiveness of synthesis-via-approximation techniques, we implemented a baseline synthesizer that works with manual summaries of smart contract actions. Specifically, we manually inspected all benchmarks whose relevant smart contracts that are all open-source and for each benchmark we allocated more than 4 manual analysis hours to extract the precise mathematical summaries. The baseline synthesizer then uses the manually extracted precise summaries to drive the synthesis.

Environment Setup: We assume that the flash loan providers are generally available, and we do not consider the borrow and the return as the part of the synthesis task. To facilitate FlashSyn experimentation, we manually annotated the prestates and poststates for each action. The details of this annotation process are described in Appendix C. Although this manual effort is required, it’s worth noting that automation of this step is possible. Techniques such as dynamic taint analysis and forward symbolic execution can be employed to automatically identify which storage variables influence the change in token balances, thereby streamlining the annotation of prestates and poststates. The experiments are conducted on an Ubuntu 22.04 server, with an AMD Ryzen Threadripper 2990WX 32-Core Processor and 128 GB RAM.

Experiment Overview. To answer RQ 1, we apply FlashSyn to the 18 benchmarks with the same set of candidate actions in ground truths. For each candidate action, the prestates and poststates are annotated for FlashSyn to drive the approximated formula for this action. We set a timeout of 3 hours for FlashSyn-poly and 4 hours for FlashSyn-inter. FlashSyn does not know a priori whether a benchmark has an attack vector with a positive profit, and it does not set any bounds on the profit. It tries iteratively to synthesize an attack vector with a maximum profit. FlashSyn’s refinement loop is guided by intermediate results and FlashSyn stops when it cannot improve the profit or the above timeouts are reached. To answer RQ 2, we replace *Approximator* component of FlashSyn with manually extracted precise mathematical summaries, and conduct the same experiment with 4 hours timeout. To answer RQ 3, we evaluate FlashSyn with different initial data points and with CEGDC enabled/disabled. To answer RQ 4, we first use FlashFind to identify candidate actions from given contract addresses which the hacker used in history, manually annotate them as in RQ 1, and then apply

Table 3: Summary of FlashSyn Results. AC denotes the number of action candidates. AP denotes the number of action candidates to approximate. GL and GP denote the length and the profit of the ground truth attack vector, respectively. IDP and TDP denote the initial and total number of collected of data points, respectively. Time denotes the time spent in seconds.

Benchmark	AC	AP	GL	GP	IDP	FlashSyn-poly			FlashSyn-inter			Precise
						TDP	Profit	Time	TDP	Profit	Time	Profit
bZx1	3	3	2	1194	5192	5849	2392	422	6373	2302 [†]	441	cs
Harvest_USDT	4	4	4	338448	8000	9325	110139 [†]	670	10289	86798 [†]	7579	cs
Harvest_USDC	4	4	4	307416	8000	8912	59614 [†]	677	10914	110051 [†]	8349	cs
Eminence	4	4	5	1674278	8000	8780	1507174	1191	8104	/	/	1606965
ValueDeFi	6	6	6	8618002	12000	19975	8378194 [†]	4691	15758	6428341 [†]	11089	cx
CheeseBank	8	3	8	3270347	2679	2937	1946291 [†]	4391	2715	1101547 [†]	10942	2816762 [†]
Warp	6	3	6	1693523	6000	6000	2773345 [†]	1164	6000	/	/	2645640 [†]
bEarnFi	2	2	4	18077	4000	4854	13770	470	4652	12329	688	13832
AutoShark	8	3	8	1381	2753	2753	1372 [†]	5484	2753	/	/	cx
ElevenFi	5	2	5	129741	4000	4070	129658	409	4326	85811	898	cx
ApeRocket	7	3	6	1345	6000	6402	1333 [†]	733	6235	1037 [†]	3238	cs
Wdoge	5	1	5	78	2000	2001	75	272	2080	75	289	75
Novo	4	2	4	24857	4000	4164	20210	702	4031	23084	861	cx
OneRing	2	2	2	1534752	4000	4710	1814882	585	4218	1942188	367	cx
Puppet	3	3	2	89000	6000	6301	89000 [†]	1203	6452	87266 [†]	1238	89000 [†]
PuppetV2	4	3	3	953100	4491	4836	747799 [†]	2441	5061	362541 [†]	2835	647894 [†]
						Solved:16/18 Avg. Time: 1594			Solved:13/18 Avg. Time: 3754			

[†]: FlashSyn’s results include at least one attack vector that differs from the ground truth.

FlashSyn with this new set of candidate actions to synthesize attack vectors under the same setting as in RQ 1. The results for RQ 1+RQ 2, RQ 3, RQ 4 are summarized in Table 3, Table 4, and Table 5, respectively.

RQ1: Effectiveness of FlashSyn. Table 3 summarizes the results of the experiment. The first five columns of Table 3 list benchmark information including the number of actions to be approximated and the length of the ground truths. The four columns under FlashSyn-poly list data concerning the synthesis using polynomial approximations. The four columns under FlashSyn-inter list data concerning the synthesis using interpolation based approximation.

Our results in Table 3 show that FlashSyn can effectively synthesize flash loan attack vectors. FlashSyn-poly (resp., FlashSyn-inter) synthesizes profitable attack vectors for 16 (resp., 13) benchmarks with an average normalized profit (w.r.t. the ground truth profit) of 0.945 (resp., 0.641). In particular, for three benchmarks (*ApeRocket*, *ElevenFi*, and *AutoShark*) the profits found by FlashSyn-poly are within 99% of the profits in the original attacks vectors. Surprisingly in another three benchmarks (*bZx1*, *Warp*, and *OneRing*) the profits found by FlashSyn are bigger than the profits in the original attacks vectors. For instance, in the *Warp* benchmark the profit is roughly double the ground truth profit (see Appendix B for *Warp* case study). On average, FlashSyn-poly is $\times 2$ faster than FlashSyn-inter, because we used parallelism in FlashSyn-poly which is not possible for FlashSyn-inter.

For 10 benchmarks, FlashSyn successfully discovers new profitable symbolic actions vectors that are different from the ground truths. These vectors either exploit the same vulnerability but

in a different order of actions, or represent arbitrage opportunities that were not exploited by the original attackers. For the remaining 6 benchmarks, FlashSyn discovers exactly the same symbolic actions vectors as the ground truths but with different parameters. Note that FlashSyn is not able to solve *Yearn* and *InverseFi* which are not shown in Table 3. These two benchmarks put high requirements on the precision of the approximation and small miss-approximation errors caused FlashSyn to miss finding attack vectors and accurate parameters.

To evaluate the efficacy of the pruning heuristics introduced in Section 5.2, we conduct experiments comparing the search space sizes when using FlashSyn with and without the application of some of the heuristics. Our results indicate that Heuristic 1 leads to an average reduction of 57% in the search space size. Subsequently, Heuristic 2 further reduces the remaining search space by an additional 34%, and Heuristic 3 contributes an additional reduction of 65% to the remaining search space.

To compare FlashSyn with existing static analyzers, we manually select contracts containing vulnerabilities in the benchmarks and apply the popular smart contracts static analyzer Slither [35] to them. In the experiments, we identify contracts that contain the root cause of the vulnerabilities as the target contracts for Slither to analyze. Note that in practice, identifying target contracts for Slither is much harder than that for FlashFind. For FlashFind, the target contracts are simply user-interface contracts. In contrast, identifying the contract with the actual vulnerability, such as a contract invoked in a deeply nested call chain, can be tedious. Slither fails to detect vulnerabilities for all 18 benchmarks, among them Slither fails to parse 2 benchmarks (Novo and Yearn). The possible reasons include: (i) Slither’s

Table 4: Summary of FlashSyn Results under Different Settings (see Appendix F for complete results). n+x: n denotes the settings of initial number of data points and +x denotes whether FlashSyn uses counterexample driven loops.

	FlashSyn-poly								FlashSyn-inter							
	200	200+x	500	500+x	1000	1000+x	2000	2000+x	200	200+x	500	500+x	1000	1000+x	2000	2000+x
Avg. Time (s)	632	893	1120	1747	842	1397	982	1594	2601	3509	3180	3917	3022	3845	3200	3754
Avg. Data Points	584	1042	1432	2376	2795	3571	5445	6367	584	1338	1432	2450	2795	3656	5445	6248
Avg. Norm. Profit	0.793	0.829	0.846	0.922	0.762	0.786	0.717	0.945	0.539	0.555	0.630	0.634	0.535	0.580	0.594	0.641
Benchmarks Solved	15	15	15	16	15	15	15	16	13	13	14	14	13	13	13	13

inability to reason across multi-contract interactions, common in flash loan attacks; and (ii) its lack of context awareness, such as not detecting Uniswap [73] when used as an oracle.

RQ2: Comparison with Precise Baseline. The last column of Table 3 lists data when the approximation component of FlashSyn is replaced with precise mathematical summaries for actions. Note that 4 benchmarks are partially closed-source (**cs**), and 5 benchmarks are too complicated (**cx**), thus we are not able to extract mathematical precise summaries for them. For others, we list the profit generated using the manually extracted mathematical expressions in the synthesizer and optimizer.

Our results in Table 3 show that the synthesis-via-approximation approach performs well compared to precise baselines. For the 9 cases that the precise baseline failed due to either close source (**cs**) or complicated contract logics (**cx**), FlashSyn found attack vectors that generate positive profits. On average, for the 7 cases that the precise baseline succeeds, the best profit from FlashSyn is 0.97 of the profit returned by the precise baseline. In particular, for *Warp* and *PuppetV2* FlashSyn synthesizes an attack vector with a profit higher than that obtained by the precise approach. This is because the approximations used in FlashSyn are simpler than the mathematical summaries used in precise baseline. This enables the optimizer to converge faster and find better parameter values within the fixed time budget.

RQ3: Counterexample Driven Approximation Refinement. Table 4 summarizes the evaluation of FlashSyn under different settings. In particular, we evaluated FlashSyn with 200, 500, 1000, and 2000 initial data points threshold per action to be approximated without and with counterexample loop. The **Avg.** rows in Table 4 are calculated based on the 16 benchmarks excluding *Yearn* and *InverseFi*. The **Avg. Norm. Profit** is calculated as the average of normalized profits, i.e., profit / ground truth profit.

For FlashSyn-poly, the results in Table 4 show that only with counterexample loop we are able to solve the 16 benchmarks (Columns **500+x** and **2000+x**). Also, the maximum average of normalized profits is achieved with counterexample loop (Column **2000+x**) which improved from 0.717 (Column **2000**) without counterexample loop to 0.945 with counterexample loop. For FlashSyn-inter, the maximum average of normalized profits is also achieved with counterexample loop (Column **2000+x**) which improved from 0.594 (Column **2000**) without counterexample loop to 0.641 with counterexample loop.

RQ4: Effectiveness of FlashFind. In this experiment, we evaluate the combination of FlashFind and FlashSyn on the 14 benchmarks that FlashSyn was able to synthesize a profitable

attack vector in Table 3 excluding the two fictional DVD benchmarks.¹³ In particular, only contract addresses are provided to FlashFind and FlashFind identifies candidate actions for FlashSyn to synthesize attack vectors with the 2000 initial data points threshold per action configuration. Table 5 presents the results.

FlashFind successfully identifies a reasonable number of action candidates for 11 out of the 14 benchmarks from given contract addresses. Among them, FlashFind identifies additional candidate actions for 7 benchmarks. For instance, FlashFind identifies 6 additional candidate actions for *OneRing*. The remaining 3 benchmarks contains action candidates whose arguments are non-primitive types, and FlashFind identifies an excessive and impractical number of choices from transaction history.¹⁴

Even with the extra candidate actions FlashSyn was able to synthesize profitable attack vectors for all 11 benchmarks. Surprisingly in 6 benchmarks, FlashSyn finds attack vectors that contains new action candidates from FlashFind that are not in the ground truth. There are two possibilities: First, the new action candidates identified by FlashFind are functionally similar to one action in ground truths (e.g. *withdraw* and *withdrawSafe* for *OneRing*). Replacing old actions with new ones gives new attack vectors. Second, the new action candidates represent another way of draining assets which the attacker failed to identify. For example, in the *Warp* benchmark, the attacker only invoked *borrowSC(USDC, v)* and *borrowSC(DAI, v)* to drain USDC and DAI [32, 64], however, FlashFind identifies *borrowSC(USDT, v)* as another candidate action, which could have been used to drain USDT as well in the same transaction.

Impact. One author of this paper collaborated with Quantstamp for applying FlashSyn for 3 months. We discovered two zero-day flash loan vulnerabilities in two protocols under audit.

Threats to Validity: The *internal* threat to validity mainly lies in human mistakes in the study. Specifically, we may understand results of FlashSyn incorrectly, or make mistakes in the implementation of FlashSyn. All authors have extensive smart contract security analysis experience and software engineering expertise in general. To further reduce this threat, we manually check the balance changes for the best results given by FlashSyn in each benchmark. We verify that with the help of on-chain exchanges, these attack vectors can generate a post-balance strictly larger than initial capital (see Appendix E). The *external* threat to validity mainly lies in the subjects used in our study. The flash loan attacks we study might not be representative. We mitigate

¹³DVD benchmarks do not have historical transactions that FlashFind can use.

¹⁴In such cases, we believe experienced security analysts could manually identify special parameters and further reduce the number of parameter choices.

Table 5: Summary of Evaluation Results of Combining FlashSyn with FlashFind. AC is the number of action candidates. AP is the number of action candidates to approximate. GL and GP are the length and the profit of the ground truth attack vector, respectively. IDP and TDP are the initial and total number of collected of data points, respectively. Time is measured in seconds.

Benchmark	GL GP		FlashFind + FlashSyn-poly						FlashSyn-poly					
			AC	AP	IDP	TDP	Profit	Time	AC	AP	IDP	TDP	Profit	Time
bZx1	2	1194	3	3	5192	5849	2392	422	3	3	5192	5849	2392	422
Harvest_USDT	4	338448	15	15	30000	34052	85593 [‡]	5514	4	4	8000	9325	110139 [†]	670
Harvest_USDC	4	307416	15	15	30000	51726	33645 [‡]	3630	4	4	8000	8912	59614 [†]	677
Eminence	4	1674278	4	4	8000	8780	1507174	1191	4	4	8000	8780	1507174	1191
ValueDeFi	6	8618002	6	6	12000	19975	8378194 [†]	4691	6	6	12000	19975	8378194 [†]	4691
Warp	6	1693523	8	5	7772	7772	2776351 [‡]	3129	6	3	6000	6000	2776351 [†]	1164
bEarnFi	4	18077	2	2	4000	4854	13770	470	2	2	4000	4854	13770	470
ApeRocket	6	1345	11	5	10000	10706	1179 [‡]	3064	7	3	6000	6402	1333 [†]	733
Wdoge	5	78	7	2	4000	4107	75 [‡]	769	5	1	2000	2001	75	272
Novo	4	24857	6	2	4000	4172	15183	791	4	2	4000	4164	20210	702
OneRing	2	1534752	8	8	16000	16614	1814877 [‡]	1104	2	2	4000	4710	1814882	585

†: FlashSyn’s results include at least one attack vector that differs from the ground truth.

‡: FlashSyn’s results include at least one attack vector that contains an action not present in the ground truth.

this risk by using diverse and reputable data sources, including academic papers [13, 60] and an industrial database [69].

Limitations: Like most synthesis tools, FlashSyn faces scalability challenges. The search space grows exponentially with the number of actions and attack vector length. A practical approach is to assess protocols on a module by module basis. By focusing only on inter-dependent actions within, we can maintain both the number of actions and the attack vector length at manageable levels, thereby mitigating the scaling issue.

8 RELATED WORK

Parametric optimization: For some flash loan attack cases, researchers [13, 60] manually extracted math formulas of function candidates, manually defined related parameter constraints, and used an off-the-shelf optimizer to search for parameters which yield the best profit. However, this technique requires significant manual efforts and expert knowledge of the underlying DeFi protocols. Consequently, it becomes impractical for checking a large number of potential attack vectors. Note that our benchmark set contains significantly more flash loan attacks than prior work [13, 60], i.e., 18 versus 2 in [60] and 9 in [13]. **Static Analysis:** Slither [35], Securify [72], Zeus [49], Park [86] and SmartCheck [71] apply static analysis techniques to verify smart contracts. There are also several works that use symbolic execution [50] to explore the program states of a smart contract, looking for an execution path that violates a user-defined invariant, e.g., Mythril [18], Oyente [53], FairCon [52], ETHBMC [41], SmartCopy [36], and Manticore [57]. These techniques tend to operate with one contract at a time and therefore cannot handle flash loan attacks that involve multiple contracts. These techniques also may suffer from the complicated logics of the DeFi contracts, and cause path explosion. FlashSyn uses its novel synthesis-via-approximation techniques to avoid these issues.

Fuzzing: ContractFuzzer [47], sFuzz [58], ContraMaster [78], SMARTIAN [16] and ItyFuzz [67] introduce novel fuzzing techniques to discover vulnerabilities in smart contracts. However, these techniques either only work on one contract or focus

on specific vulnerabilities like re-entrancy. Moreover, flash loan attack vectors can contain up to 8 actions and 7 integer parameters, which is unlikely to be found by random fuzzing.

Flash Loan Attacks: Prior works [13, 60, 79] study specific flash loan attacks and manually analyze and optimize the attack vectors. Some other tools [63, 76, 83] are designed to monitor flash loan attacks after they happened. Other researchers investigate other usage of flash loans including arbitrage [77] or wash trading [44]. To the best of our knowledge, FlashSyn is the first tool that can detect flash loan attacks before they happen and show successes in real-world DeFi protocols under auditing.

9 CONCLUSION

We have proposed an automated synthesis framework based on numerical approximation to generate the flash loan attack vectors on DeFi protocols. Our results of FlashSyn show that the proposed framework is practical and FlashSyn can automatically synthesize attack vectors for real world attacks. Our results also highlight the effectiveness of the synthesis-via-approximation approach. The approach helps FlashSyn to overcome the challenges posed by complicated functions in DeFi protocols and our results demonstrate that using approximations of these functions is sufficient to drive the synthesis process. FlashSyn has been adopted by a top smart contract auditing company to detect flash loan vulnerabilities. The paper also points out a new promising direction for solving trace synthesis problems when facing complicated functions.

10 DATA AVAILABILITY

The benchmarks, source code and experimental data of our artifacts are publicly accessible on [14] and have been archived on [15].

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A FUNCTIONS OF CURVE.FI Y POOL CONTRACT

To extend the discussion about the complexity of (Curve.Fi Y Pool) contract in Section 3 , we include another three functions *exchange_underlying*, *_exchange*, and *get_y* in Figure 4, Figure 5, and Figure 6 respectively.

exchange_underlying is the public function usually called by users to exchange *dx* amount of underlying asset *i* to *j*, and *min_dy* represents the minimum quantity expected to receive from the exchange. Once *exchange_underlying* is called, it will internally execute a private function *_exchange*, which will call another private *get_y*. *get_y* first calls *get_D* to calculate a constant *D* iteratively. Then it calculates an updated value of *y* iteratively based on *D* and other constants. This iterative Calculation impedes symbolic execution since it results in too complicated non-linear constraints.

```

1 function exchange_underlying( int128 i, int128 j,
2                               uint dx, uint min_dy)
3 {
4     uint[] memory rates = _stored_rates();
5     uint N_COINS = rates.length;
6     uint[] memory precisions = PRECISION_MUL;
7     uint rate_i = rates[i] / precisions[i];
8     uint rate_j = rates[j] / precisions[j];
9     uint dx_ = (dx * PRECISION) / rate_i;
10    // key step: call get_y and then call get_D
11    uint dy_ = _exchange(i, j, dx_, rates);
12    uint dy = (dy_ * rate_j) / PRECISION;
13    assert(dy >= min_dy, "...");
14    bool[] memory tethered = TETHERED;
15    uint ok = 0;
16    if (tethered[i])
17        USDT(u_coins[i]).transferFrom(
18            msg.sender, address(this), dx);
19    else
20        assert_modifiable(
21            ERC20(u_coins[i]).transferFrom(
22                msg.sender, address(this), dx)
23        );
24    ERC20(u_coins[i]).approve(coins[i], dx);
25    yERC20(coins[i]).deposit(dx);
26    yERC20(coins[j]).withdraw(dy_);
27    dy=ERC20(u_coins[j]).balanceOf(address(this));
28    assert(dy >= min_dy, "...");
29    if (tethered[j])
30        USDT(u_coins[j]).transfer(msg.sender, dy);
31    else assert_modifiable(ERC20(u_coins[j])
32        .transfer(msg.sender, dy));
33    log.TokenExchangeUnderlying(msg.sender, i, dx, j, dy);
34 }

```

Figure 4: Source code of *exchange_underlying()*. Original code is in Vyper, rewritten in Solidity.

```

1 function _exchange(int128 i, int128 j,
2                   uint dx, uint[] calldata rates)
3 {
4     uint[N_COINS] xp = _xp(rates);
5     uint x = xp[i] + dx * rates[i] / PRECISION;
6     uint y = get_y(i, j, x, xp);
7     uint dy = xp[j] - y;
8     uint dy_fee = dy * self.fee / FEE_DENOMINATOR;
9     uint dy_admin_fee = dy_fee * self.admin_fee /
10        FEE_DENOMINATOR;
11    balances[i] = x * PRECISION / rates[i];
12    balances[j] = (y + (dy_fee - dy_admin_fee)) * PRECISION /
13        rates[j];
14    uint _dy = (dy - dy_fee) * PRECISION / rates[j];
15    return _dy;
16 }

```

Figure 5: Source code of *exchange()*. Original code is in Vyper, rewritten in Solidity.

```

1 function get_y( int128 i, int128 j,
2                uint x, uint[] calldata _xp) returns (uint)
3 {
4     uint N_COINS = _xp.length;
5     assert(
6         i != j && i >= 0 && j >= 0 &&
7         uint(i) < N_COINS && uint(j) < N_COINS
8     );
9     uint D = get_D(_xp);
10    uint c = D;
11    uint S_ = 0;
12    uint Ann = A * N_COINS; // A is a constant
13    uint _x = 0;
14    for (uint _i = 0; _i < N_COINS; _i = _i + 1) {
15        if (_i == uint(i)) {
16            _x = x;
17        } else if (_i != uint(j)) {
18            _x = _xp[_i];
19        } else continue;
20        S_ += _x;
21        c = (c * D) / (_x * N_COINS);
22    }
23    c = (c * D) / (Ann * N_COINS);
24    uint b = S_ + D / Ann; // - D
25    uint y_prev = 0;
26    uint y = D;
27    for (uint _i = 0; _i < 255; _i = _i + 1) {
28        y_prev = y;
29        y = (y * y + c) / (2 * y + b - D);
30        // Equality with the precision of 1
31        if (y > y_prev) {
32            if (y - y_prev <= 1) break;
33        } else {
34            if (y_prev - y <= 1) break;
35        }
36    }
37    return y;
38 }

```

Figure 6: Source code of *get_y()*. Original code is in Vyper, rewritten in Solidity.

B WARP FINANCE CASE STUDY

On Dec. 18, 2020, Warp Finance suffered a flash loan attack which leads to about \$7.8 million loss, according to Rekt [64]. The first attack happened in the transaction [32]. A detailed postmortem analysis [68] is written by SlowMist on Medium.

Attack Root Cause: The core of Warp attack is a design flaw of calculating the price of LP tokens. The price of LP token is calculated as $(\text{amount}(\text{WETH}) \text{ in the pool} * \text{WETH price} + \text{amount}(\text{DAI}) \text{ in the pool} * \text{DAI price}) / \text{total supply of LP}$. Even though the developer uses Uniswap official price oracle to (correctly) calculate the prices of WETH and DAI, they failed to realize the amounts of WETH and DAI can also be manipulated by flash loans. The exploiter took advantage of this point, pumped up the LP price, and falsely borrow excessive USDC and DAI from the pool.

Real Attack Vector in History:

Action 1: *mint(2900030e18)*

Action 2: *swap(WETH, DAI, 341217e18)*

Action 3: *provideCollateral(94349e18)*

Action 4: *borrowSC(USDC, 3917983e6)*

Action 5: *borrowSC(DAI, 3862646e18)*

Action 6: *swap(DAI, WETH, 47622329e18)*

Adjusted profit: 1,693,523 USD (DAI + USDC + WETH)

First the exploiter flash loaned WETH and DAI and *mint* 2900030 DAI and equivalent WETH to Uniswap's WETH-DAI pair. Then the attacker swapped a huge amount of WETH into DAI via the pair to increase the total value of the WETH-DAI pool, pumping up the unit price of LP token. The exploiter then mortgages the previously obtained LP Token through the *provideCollateral* function. As the unit price of LP Token becomes higher, the LP tokens mortgaged by the attacker give an abnormally high borrow limit thus the attacker can borrow more make profit.

Best Attack Vector from FlashSyn:

Action 1: *swap(WETH, DAI, 480069e18)*

Action 2: *mint(322007e18)*

Action 3: *provideCollateral(65937e18)*

Action 4: *borrowSC(USDC, 3862530e6)*

Action 5: *borrowSC(DAI, 3917914e18)*

Action 6: *swap(DAI, WETH, 48862671e18)*

Adjusted profit: 3,368,718 USD (DAI + USDC + WETH)

It is quite surprising that the attack vector from FlashSyn gets a higher profit compared to the attacker in history. The reason behind this is the attack vector given by FlashSyn spends more on manipulating Uniswap pair (Action 1 and Action 6) and spends less on the LP Token mortgaged (Action 2 and Action 3). In this attack, to get the same borrow limit (which can be used to borrow USDC and DAI in Action 4 and Action 5), it is more economical to spend on manipulating the Uniswap pair than collateralizing more LP tokens.

C ANNOTATE ACTION CANDIDATES

As discussed in Section 3, FlashSyn makes use of annotations of prestates and poststates to drive the approximations. This section provides more details about the annotation process.

In principle, **states** refer to read-only functions or contract variables that contribute to the calculation of token transfers. A **prestate** refers to the state before the execution of an action candidate. If two executions share identical prestates and related inputs, their token transfers must also be the same. FlashSyn approximates a function which maps (prestates, inputs) to token

transfers. Executing an action will also alter states, which are denoted as **poststates**. Poststates of an action will be the prestates of the next action. FlashSyn also approximates a function which maps (prestates, inputs) to poststates. By utilizing these two types of approximations, FlashSyn automatically builds a constrained optimization problem to search for the optimal parameters.

Here we use the Vault contract in Figure 7 as an example to illustrate how we annotate *deposit* and *withdraw* functions.

Function *deposit* moves two tokens. First, it transfers amount USDC from *msg.sender*, which is exactly the input argument. No further annotation is needed for this token transfer. Second, it mints and transfers toMint fUSDC tokens to the *msg.sender*. We also find toMint is calculated using the input amount and two functions *totalSupply()* and *underlyingBalanceWithInvestment()*.

totalSupply() returns contract variable *totalSupply* so it is not further expandable. *underlyingBalanceWithInvestment()* can be further expanded to another two read-only functions *underlyingBalanceInVault()* and *investedUnderlyingBalance()*. Both functions are not further expandable because they are external read-only function calls.

It is also observed that *totalSupply()*, *underlyingBalanceInVault()* are changed after the execution of *deposit*, while *investedUnderlyingBalance()* remains unchanged. Thus, we annotate *deposit* as follows:

```
prestates= {totalSupply(), underlyingBalanceInVault(),
            , investedUnderlyingBalance()},
poststates= {totalSupply(), underlyingBalanceInVault()},
tokenIn = {USDC}, tokenOut = {fUSDC}.
```

Function *withdraw* also moves two tokens. First, it transfers and burns *numberOfShares* fUSDC tokens from *msg.sender*. *numberOfShares* is just the input argument.

Second, it transfers *underlyingAmountToWithdraw* USDC tokens to *msg.sender*. *underlyingAmountToWithdraw* is calculated using the input *numberOfShares* and two states *totalSupply()* and *underlyingBalanceWithInvestment()*. Similarly, *underlyingBalanceWithInvestment()* can be further expanded to *underlyingBalanceInVault()* and *investedUnderlyingBalance()*.

We also observe that *totalSupply()*, *underlyingBalanceInVault()* are changed after the execution of *withdraw*, while *investedUnderlyingBalance()* remains unchanged. Thus, we annotate *withdraw* as follows:

```
prestates= {totalSupply(), underlyingBalanceInVault(),
            , investedUnderlyingBalance()},
poststates= {totalSupply(), underlyingBalanceInVault()},
tokenIn = {fUSDC}, tokenOut = {USDC}.
```

In some cases, action A may internally call another function B from a different contract, which ultimately results in token transfers to/from users. In such scenarios, we need to annotate function B as the annotations for action A. Additionally, there may be instances where action C alters the states of another action D, despite not belonging to the same protocol. For instance, action D could utilize action C's contract states as an oracle, and action C may modify these states. In such situations, it is

```

1 function totalSupply() public view returns (uint256) {
2     return _totalSupply;
3 }
4
5 function underlyingBalanceInVault() view public returns (uint256) {
6     return IERC20(underlying()).balanceOf(address(this));
7 }
8
9 function underlyingBalanceWithInvestment() view public returns
10     (uint256) {
11     if (address(strategy()) == address(0)) {
12         return underlyingBalanceInVault();
13     }
14     return underlyingBalanceInVault()
15         .add(IStrategy(strategy()).investedUnderlyingBalance());
16 }
17 function deposit(uint256 amount) external {
18     _deposit(amount, msg.sender, msg.sender);
19 }
20
21 function _deposit(uint amount, address sender, address beneficiary)
22     internal {
23     uint toMint = totalSupply() == 0 ? amount:
24
25         amount.mul(totalSupply()).div(underlyingBalanceWithInvestment());
26     _mint(beneficiary, toMint);
27     IERC20(underlying()).safeTransferFrom(sender, address(this),
28         amount);
29     emit Deposit(beneficiary, amount);
30 }
31
32 function withdraw(uint numberOfShares) external {
33     uint totalSupply = totalSupply();
34     _burn(msg.sender, numberOfShares);
35     uint underlyingAmountToWithdraw =
36         underlyingBalanceWithInvestment()
37         .mul(numberOfShares)
38         .div(totalSupply);
39     if (underlyingAmountToWithdraw > underlyingBalanceInVault()) {
40         if (numberOfShares == totalSupply) {
41             IStrategy(strategy()).withdrawAllToVault();
42         } else {
43             uint missing = underlyingAmountToWithdraw.sub(
44                 underlyingBalanceInVault()
45             );
46             IStrategy(strategy()).withdrawToVault(missing);
47         }
48         // recalculate to improve accuracy
49         underlyingAmountToWithdraw = Math.min(
50             underlyingBalanceWithInvestment().mul(numberOfShares).div(
51                 totalSupply
52             ),
53             underlyingBalanceInVault()
54         );
55     }
56     IERC20(underlying()).safeTransfer(msg.sender,
57         underlyingAmountToWithdraw);
58     emit Withdraw(msg.sender, underlyingAmountToWithdraw);
59 }

```

Figure 7: The Vault *deposit* and *withdraw* methods.

essential to include action D’s prestates in action C’s annotations. We would then collect data points for these state changes and approximate them separately in the approximation stage.

We believe that the annotating process should not pose significant difficulties for security analysts. Furthermore, we are optimistic that this process can be further automated through either static analysis of (open-source) contracts or dynamic

analysis of the EVM level execution traces of deployed contracts (closed-source), and is left as future work.

D FLASHFIND: ACTION CANDIDATES IDENTIFICATION

Flash loan attacks typically focus on victim contracts containing functions capable of transferring tokens,¹⁵ which can be invoked by regular users. The attacker manipulates the transfer amount under specific conditions. The mathematical models of victim contracts vary across different protocols.

Specifically, smart contracts with lending, leveraging, or yield-earning functions are more vulnerable to flash loan attacks. This susceptibility arises from the involvement of token transfers outside these contract types. Basic DeFi lego contracts, such as stable coins, Uniswap, and Curve.fi, are unlikely to be targeted in flash loan attacks due to their fundamental role as building blocks and infrastructure of nearly all DeFi protocols. These contracts have undergone exclusive audits and have been in use for several years.

Given a set of target smart contracts, FlashFind helps users of FlashSyn in selecting a set of action candidates likely to be involved in an attack vector.

D.1 Selecting Action Candidates from Contract Application Binary Interfaces (ABIs)

The Application Binary Interface (ABI) serves as an interpreter enabling communication with the EVM bytecode. For all deployed and verified smart contracts on the blockchain, their ABIs are made public to facilitate user interactions by allowing them to call functions and engage with the contracts. An ABI typically comprises (public or external) function names, argument names/types, function state mutability, and return types.

During the process of selecting action candidates, certain functions can be safely ignored for the following reasons:

- Functions with the view or pure mutability can be excluded as they do not modify the state of contracts.
- Functions that can only be invoked by privileged users, such as *transferOwnership*, *changeImplementation*, and *changeAdmin*, can also be disregarded since they are unlikely to be accessed by regular users¹⁶. This step can also be accomplished by conducting a lightweight static analysis on the source code of the contracts.
- Token permission management functions/parameters, such as the *approve* function or parameters like *deadline* and *amountOutMin*, are excluded. These functions/parameters solely control whether a transaction will be reverted or not and do not affect the functional behaviors of contracts. To simplify the search process of FlashSyn, these permissions are assumed to be granted maximally.

¹⁵Here, tokens refer to various forms of DeFi tokens, including stable coins, debt tokens, share tokens, liquidity tokens, asset tokens, etc.

¹⁶Previous works [45, 51] have extensively researched access control vulnerabilities, which are outside the scope of this work.

D.2 Learning Special Parameters from Transaction History

After selecting a set of action candidates from contracts’ ABIs, some non-integer parameters (eg. bytes, string, address, array, enum) can still be unknown. FlashFind collects past transactions of the target contracts using TrueBlocks [66] and Blockchain Explorers([34], [10], [43]). Subsequently, FlashFind extracts function level trace data from these transactions using Phalcon¹⁷[2], and utilizes this data to learn the special parameters from previous function calls made to the contract.

D.3 Local Execution and Intra-dependency Analysis

Following the selection of action candidates and determination of action parameters, each action candidate is executed in a forked blockchain (foundry [40]) to verify its executability at a given block. An action candidate may not be executable due to various reasons: (1) the function is disabled by the owner or admin; (2) internal function calls to other contracts are disabled by the owners or admins of those contracts; (3) the function is not valid under current blockchain states. The inexecutability due to these reasons cannot be identified by static analysis of source code and can only be determined by executions. All such inexecutable functions are filtered out.

During this step, we focus solely on ensuring the executability of functions at the given block, without considering their profitability. FlashFind automatically collects storage read/write information during the execution of these functions and infers the Read-After-Write (RAW) dependencies¹⁸ between different action candidates. An action A has a RAW dependency (or equivalently, is RAW dependent) on action B if the execution of action A reads the storage written by action B¹⁹. From the RAW dependencies, it is possible to observe that certain functions behave independently, meaning they do not have any RAW dependencies on other functions, and other functions do not have any RAW dependencies on them either. Consequently, these independent functions can be safely ignored.

After analyzing ABIs, transaction history, and local executions, FlashFind generates a list of action candidates with only their integer arguments left undetermined. These action candidates are then input into FlashSyn for further synthesis.

D.4 FlashFind Algorithm

Algorithm 3 describes the overall procedure FlashFind to identify candidate actions. FlashFind takes as inputs a list of contract addresses `contracts` that are used by a DeFi protocol and a block height `bh`. It then produces a list of functions `dependentFunctions` that constitute candidate actions.

Algorithm 3: FlashFind to identify candidate actions. It takes a list of contract addresses `contract`, a block height `bh`, and outputs a list of candidate actions (functions), along with their RAW dependencies.

```

1: procedure FLASHFIND(contracts, bh)
2:   functions  $\leftarrow$  [ ];
3:   traces  $\leftarrow$  [ ];
4:   for each A  $\in$  contracts;
5:     functions[A]  $\leftarrow$  ANALYZEABI(A)
6:     transactionHistory  $\leftarrow$  COLLECTTRANSACTIONS(A, bh);
7:     functions[A].add(FILTER(transactionHistory));
8:     for each a  $\in$  functions[A];
9:       storageAccess[a]  $\leftarrow$  EXECUTE(a, bh)
10:    dependentFunctions  $\leftarrow$  [ ];
11:    for each a  $\in$  storageAccess.keys;
12:      for each b  $\neq$  a  $\in$  storageAccess.keys;
13:        if CHECKDEPENDENCY(storageAccess[a], storageAccess[b])
14:          dependentFunctions[a].add(b)
15:    return dependentFunctions

```

The procedure FlashFind first analyzes each contract’s ABIs and identifies a list of non-privileged²⁰ non-read-only functions with only integer arguments or no arguments. Then FlashFind inspects the blockchain state and collects the function level trace data for all historical transactions that occurred before the block height `bh` for every contract listed in `contracts` using the sub-procedures COLLECTTRANSACTIONS (line 6). Using the trace data, we then leverage the sub-procedure FILTER to identify non-integer arguments for other non-privileged non-read-only functions of contract `A`, and these functions, with only their integer parameters undetermined, are flagged as additional candidate actions (line 7). We then execute these candidate actions locally to verify their executability via the sub-procedure EXECUTE, while collecting their storage read/write information (line 9). For each two functions `a` and `b`, we check if `a` is RAW dependent on `b` via the subprocedure CHECKDEPENDENCY (line 13). If so, we add `b` to the list of functions that `a` depends on (line 14). Finally, FlashFind returns the list of functions(keys of `dependentFunctions`), along with their RAW dependencies (values of `dependentFunctions`) (line 15).

D.5 Evaluation Results

We conducted an evaluation of FlashFind and FlashSyn combined on 14 historical flash loan attack benchmarks solved by FlashSyn alone. The detailed results are presented in Table 5 of main text. Notably, FlashFind and FlashSyn together successfully solved 11 benchmarks. Surprisingly, for 6 benchmarks, FlashFind discovered new attack vectors containing new actions that were not utilized by the original attackers. These new attack vectors exploit the same vulnerabilities and prove to be profitable as well, highlighting the effectiveness of FlashFind in identifying action candidates.

However, there were 3 benchmarks where FlashFind failed to identify the correct set of action candidates. We discuss the reasons behind these failures below. For ElevenFi, there is a function *addLiquidity* which requires an argument *amounts* of

¹⁷Phalcon is a transaction explorer that provides functional level trace data.

¹⁸This RAW dependency information is also employed in FlashSyn’s initial data collection to expand the range of data points.

¹⁹It is important to note that this step excludes any tx.origin/msg.sender-related storage reads/writes, as such storage accesses do not alter the state of the protocol and are therefore unlikely to impact the functional behaviors of actions.

²⁰Privileged functions refer to functions that can only be called by privileged users, e.g., owners of the contract, or within a certain range of blocks. Thus, these functions are not likely to be used by an attacker with an arbitrary address.

integer array of length 4. For AutoShark, a function *deposit* takes an address argument *referrer*. For CheeseBank, a function *refresh* takes an argument *symbols* which is a array of strings. After analyzing their past transactions, we find there are too many possible values for these non-integer arguments. Thus, we cannot learn the special parameters from transaction history. While experienced security analysts might manually identify these special parameters and include them in the action candidates, we view these instances as failures of FlashFind, as our goal is to automate the process as much as possible.

E PROFIT CALCULATION AND FLASH LOAN PAYMENT

As discussed in Section 4, FlashSyn uses constant token prices to calculate the profit of an attack vector. A positive profit indicates flash loan vulnerabilities inside the contracts. We notice two possible concerns regarding this assumption.

First, the price of a token might be influenced by an attack vector; thus FlashSyn’s profit calculation might be inaccurate. As a result, there might be false positives in the results. In fact, hackers typically prefer to keep their final profit in stable coins or popular blockchain-native tokens such as Ethereum, Bitcoin, or BNB. This preference arises from the fact that other derivative tokens associated with victim protocols become worthless after the hack.

Second, if we require all initial balances of an attacker is from flash loans, a positive profit then does not necessarily mean the ability to pay back flash loan, since the final balances could not be strictly larger than the initial balances. In historical flash loan attacks, the attackers usually choose to convert some of their profit to what’s being flash loaned, for paying back the flash loan.

We designed an experiment to validate our results and justify our assumption. A summary of the experiment is shown in Table 6. For each benchmark, we select the attack vector with the best profit returned by FlashSyn under all different settings. We record their final balances under "**Results of FlashSyn**" column. We observe for 8 benchmarks, their final balance can already cover the initial balance; thus the profit calculation is valid here, since it directly represents the increase of the attacker’s balances.

Apart from two security challenges(Puppet, PuppetV2), we tried to manually implement DEX swaps after the attack vectors, to make sure final balances are strictly larger than initial balances. Practically, we use 1inch [1] and Curve.Finance [23, 37] for Ethereum benchmarks, and Pancake Swap [70] for Binance benchmarks. Results after swapping are listed under "**Results after Swapping**" column. For 6 benchmarks, we successfully implement DEX swaps so that their final balances are strictly larger than initial balances. We observe the profit calculation does not change a lot after swapping, which represents the attack vectors found by FlashSyn do yield positive profit and indicate flash loan vulnerabilities.

Overall, among 16 historical flash loan attack benchmarks, FlashSyn synthesized attack vectors with positive profit for 14

cases. And 13 of them are valid even under the consideration of flash loan payment.

F FLASHSYN RESULTS UNDER DIFFERENT SETTINGS

We applied FlashSyn to 18 benchmarks, we set a time limit of 1 hour for initial data collection and another time limit of 2(resp., 3) hours for the rest of the synthesis procedure. In Section 7, due to page limit, we are only able to show a summary of our experiment results. Here we show all the results of our experiment under different settings and for all benchmarks. The profit of best attack vectors found by FlashSyn under different settings is listed in Table 7. The synthesis time is listed in Table 8. The initial data collection time is listed in Table 9.

Note in Section 7, we add synthesis time and initial data collection time together to get the total time, while Table 7 and Table 8 list them separately.

Table 6: Summary of Repaying Flash Loan(Legends: “Initial Balance” represents initial token balances at the start of FlashSyn. “Profit” represents adjusted calculated using constant token prices. “Pay Back?” represents whether final token balances are strictly greater than initial balances.)

benchmark	Initial Balance	Results of FlashSyn	Profit	Pay Back?	Result after Swapping	Profit	Pay Back?
bZx1	112 WBTC 4500 ETH	59 WBTC 9009 ETH	2438	✗*	/	/	/
Harvest_USDT	50000000 USDT 20000000 USDC	52635352 USDT 17502461 USDC	137813	✗	50000000 USDT 20139106 USDC	139106	✓
Harvest_USDC	18308555 USDT 50000000 USDC	15106415 USDT 53312192 USDC	110051	✗	18415434 USDT 50000000 USDC	106878	✓
Warp	500000 WETH 5000000 DAI	3917914 USDC 493733 WETH 8472025 DAI	3368718	✗	504549 WETH 5000000 DAI	2918865	✓
ValueDeFi	116000000 DAI 100000000 USDT	102223937 DAI 69829957 USDT 32023919 USDC 20300381 CRV	8378194	✗	116000000 DAI 108225064 USDT	8225064	✓
Yearn	130000000 DAI 134000000 USDC	/	/	/	/	/	/
Eminence	15000000 DAI	1601468 DAI	1601468	✓	/	/	/
CheeseBank	21000 ETH	20550 ETH 1435304 USDC 710427 USDT 0 DAI	1946291	✗	25493 ETH	1991297	✓
InverseFi	27000 WBTC	/	/	/	/	/	/
ElevenFi	130001 BUSD	259742 BUSD	129741	✓	/	/	/
bEarnFi	7804239 BUSD	7818022 BUSD	13783	✓	/	/	/
ApeRocket	1615000 CAKE	16849 WBNB 1276757 CAKE	1333	✓	1553 WBNB 1615000 CAKE	1553	✓
AutoShark	100001 WBNB	101373.63 WBNB	1372	✓	/	/	/
Novo	2000 WBNB	25084 WBNB	23084	✓	/	/	/
Wdoge	3000 WBNB	3078 WBNB	78	✓	/	/	/
OneRing	150000000 USDC	151893085 USDC	1893085	✓	/	/	/
Puppet	1000 DVT 25 ETH	100000 DVT 15 ETH	89000	✗**	/	/	/
PuppetV2	10000 DVT 20 ETH	886996 DVT 1 ETH 0 WETH	857996	✗**	/	/	/

*: bZx1 attack is the earliest flash loan attack (ETH block 9484688) among all benchmarks, and we fail to find DEX with enough liquidity to perform the swap in the same transaction. In history, after the exploit, bZx1 attacker purchased WBTC in small amounts over two days on DEX, to repay the WBTC borrowed.

** : Unlike other benchmarks, Puppet and PuppetV2 are community security challenges instead of flash loan attacks in history. We don't consider paying back flash loan in these two cases.

Table 7: Profit Summary under Different Settings (N and N+X represent running FlashSyn with N initial data points for each action, with CEGDC disabled and enabled respectively.)

benchmark	historyProfit	FlashSyn-poly							
		200	200+X	500	500+X	1000	1000+X	2000	2000+X
bZx1	1194	2228	2443	2393	2336	2372	2446	2339	2392
Harvest_USDT	338448	117137	121132	136993	119232	137606	120713	137813	110139
Harvest_USDC	307416	53890	73021	88922	79355	90186	75377	59614	59614
Warp	1693523	2778266	2969630	3368718	3368718	3290458	3290458	2773345	2773345
ValueDeFi	8618002	5512992	5512992	6919868	8088716	4831255	8307800	2562183	8378194
Yearn	56924	/	/	/	/	/	/	/	/
Eminence	1674278	1524534	1601468	1116830	1387119	1258248	1121077	585029	1507174
CheeseBank	3270347	1675958	1675958	1675958	1675958	1675958	1675958	1675958	1946291
InverseFi	2515606	/	/	/	/	/	/	/	/
ElevenFi	129741	118025	129741	129741	129741	104279	105149	129741	129658
bEarnFi	18077	13783	13730	13783	13756	13783	13715	13783	13770
ApeRocket	1345	704	704	/	1323	700	700	1333	1333
AutoShark	1381	/	/	1346	1346	/	/	/	1372
Novo	24857	14907	14907	17146	17146	14835	14835	14835	20210
Wdoge	78	75	75	75	75	75	75	75	75
OneRing	1534752	1673425	1673425	1814877	1814877	628440	628440	590506	1814882
Puppet	89000	85093	85092	84095	84096	89000	78200	89000	89000
PuppetV2	953100	760543	835148	326400	400830	647894	857996	400965	747799
Solved:		15	15	15	16	15	15	15	16
Avg. Normalized. Profit:		0.793	0.829	0.846	0.922	0.762	0.786	0.717	0.945

benchmark	historyProfit	FlashSyn-inter							
		200	200+X	500	500+X	1000	1000+X	2000	2000+X
bZx1	1194	2018	2383	2364	2364	2231	2294	2301	2302
Harvest_USDT	338448	739	10759	6981	13944	12043	72597	1544	86798
Harvest_USDC	307416	506	14338	65670	506	505	2125	504	110051
Warp	1693523	/	/	596570	596570	/	/	/	/
ValueDeFi	8618002	5415559	5415559	8348059	8348059	287732	3468019	6428341	6428341
Yearn	56924	/	/	/	/	/	/	/	/
Eminence	1674278	/	/	/	/	/	/	/	/
CheeseBank	3270347	659895	659895	952455	1068853	1045789	1339468	1101547	1101547
InverseFi	2515606	/	/	/	/	/	/	/	/
ElevenFi	129741	57510	57510	65090	86687	94456	94456	85811	85811
bEarnFi	18077	11448	11448	12695	11787	11576	12059	11335	12329
ApeRocket	1345	1323	1323	1333	1333	1135	1135	1037	1037
AutoShark	1381	/	/	/	/	/	/	/	/
Novo	24857	14317	14317	12196	13891	14065	14065	23084	23084
Wdoge	78	74	74	78	78	75	75	75	75
OneRing	1534752	1893085	1893085	1830059	1891589	1888510	1888510	1814877	1942188
Puppet	89000	81576	82560	78818	78821	81172	81172	87266	87266
PuppetV2	953100	344943	224177	459980	459980	397256	397256	362540	362541
Solved:		13	13	14	14	13	13	13	13
Avg. Normalized. Profit:		0.539	0.555	0.630	0.634	0.535	0.580	0.594	0.641

Table 8: FlashSyn’s Synthesis Time Summary under Different Settings.

Time(s)	FlashSyn-poly								FlashSyn-inter							
	benchmark	200	200+X	500	500+X	1000	1000+X	2000	2000+X	200	200+X	500	500+X	1000	1000+X	2000
bZx1	111	379	115	271	131	454	119	321	159	357	146	327	160	1634	129	340
Harvest_USDT	144	636	295	1176	376	621	320	548	3981	7940	5985	8380	5363	7867	5616	7457
Harvest_USDC	188	554	365	991	350	451	420	561	3662	7611	5845	8400	5526	7845	5476	8233
Warp	593	1484	1319	1542	1175	1428	965	1069	/	/	3320	5446	/	/	/	/
ValueDeFi	1098	1079	826	5339	927	3669	1145	4402	10800	10800	10800	10800	10800	10800	10800	10800
Yearn	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/
Eminence	468	1525	461	1251	1025	1209	460	1094	/	/	/	/	/	/	/	/
CheeseBank	4311	4080	4811	5586	4648	6379	5022	4249	9840	10800	10800	10800	10800	10800	10800	10800
InverseFi	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/
ElevenFi	131	298	156	300	139	1352	132	288	457	875	463	834	374	2443	381	777
bEarnFi	123	359	118	601	155	731	162	439	352	673	569	950	664	666	517	657
ApeRocket	230	409	/	610	224	529	416	652	2057	3132	2342	3724	1921	3047	1920	3157
AutoShark	/	/	4485	5762	/	/	/	5348	/	/	/	/	/	/	/	/
Novo	239	420	524	721	330	512	383	630	468	740	796	879	482	848	657	789
Wdoge	89	203	170	299	145	377	136	237	117	263	226	427	106	385	217	254
OneRing	92	192	183	378	120	309	159	526	110	259	194	485	97	383	169	308
Puppet	36	68	37	65	21	41	32	83	86	197	72	158	89	146	65	118
PuppetV2	45	133	48	132	35	75	37	103	233	484	196	456	218	437	220	497
Avg.Time(s)	527	788	928	1564	653	1209	661	1284	2486	3395	2982	3719	2815	3639	2844	3399

Table 9: FlashSyn’s Initial Data Collection Time Summary under Different Settings.

Initial Data Collection(s)				
	benchmark	200	500	1000
bZx1	49	73	91	101
Harvest_USDT	37	49	74	122
Harvest_USDC	62	76	68	116
Warp	33	45	60	95
ValueDeFi	80	113	172	289
Yearn	168	189	217	299
Eminence	56	63	73	97
CheeseBank	91	94	107	142
InverseFi	52	62	91	152
ElevenFi	69	72	95	121
bEarnFi	15	15	23	31
ApeRocket	29	36	48	81
AutoShark	99	97	123	136
Novo	36	42	51	72
Wdoge	10	14	21	35
OneRing	17	22	36	59
Puppet	220	633	686	1120
PuppetV2	773	1482	1218	2338
Avg. Time:	105	176	181	300

Table 10: Number of Total Data Points under Different Settings(N(M) represents the number of data points is N after M rounds of CEGDC.)

benchmark	FlashSyn-poly							
	200	200+X	500	500+X	1000	1000+X	2000	2000+X
bZx1	600	1788	1500	2273	3000	3892	5192	5849
Harvest_USDT	800	2002	2000	3704	4000	5330	8000	9325
Harvest_USDC	800	3004	2000	3561	4000	4695	8000	8912
Warp	600	604	1500	1500	3000	3001	6000	6000
ValueDeFi	1200	1200	3000	11138	6000	13060	12000	19975
Yearn	/	/	/	/	/	/	/	/
Eminence	800	1525	2000	2663	4000	4659	8000	8780
CheeseBank	464	464	942	715	1534	1770	2679	2937
InverseFi	/	/	/	/	/	/	/	/
ElevenFi	400	460	1000	1077	2000	2078	4000	4070
bEarnFi	400	1444	1000	2066	2000	2744	4000	4854
ApeRocket	600	630	1500	1739	3000	3223	6000	6402
AutoShark	478	478	1068	1068	1645	1645	2753	2753
Novo	400	578	1000	1110	2000	2072	4000	4164
Wdoge	200	201	500	501	1000	1001	2000	2001
OneRing	400	662	1000	1386	2000	2188	4000	4710
Puppet	600	712	1500	1585	3000	3111	6000	6301
PuppetV2	600	914	1396	1936	2534	2664	4491	4836
Avg. data points:	584	1042	1432	2376	2795	3571	5445	6367

benchmark	FlashSyn-inter							
	200	200+X	500	500+X	1000	1000+X	2000	2000+X
bZx1	600	1965	1500	3028	3000	4413	5192	6373
Harvest_USDT	800	3367	2000	4811	4000	6567	8000	10289
Harvest_USDC	800	3687	2000	5240	4000	7231	8000	10914
Warp	600	600	1500	1500	3000	3000	6000	6000
ValueDeFi	1200	1200	3000	5974	6000	9281	12000	15758
Yearn	/	/	/	/	/	/	/	/
Eminence	800	923	2000	2080	4000	4109	8000	8104
CheeseBank	464	464	942	1099	1534	1635	2679	2715
InverseFi	/	/	/	/	/	/	/	/
ElevenFi	400	759	1000	1341	2000	2363	4000	4326
bEarnFi	400	1762	1000	2848	2000	2696	4000	4652
ApeRocket	600	1659	1500	2426	3000	3309	6000	6235
AutoShark	478	478	1068	1500	1645	1645	2753	2753
Novo	400	412	1000	1035	2000	2028	4000	4031
Wdoge	200	431	500	654	1000	1137	2000	2080
OneRing	400	656	1000	1284	2000	2218	4000	4218
Puppet	600	1244	1500	2012	3000	3509	6000	6452
PuppetV2	600	1806	1396	2369	2534	3348	4491	5061
Avg. data points:	584	1338	1432	2450	2795	3656	5445	6248