Towards Understanding Flash Loan and Its Applications in DeFi Ecosystem

Dabao Wang*
Zhejiang University
Hangzhou, Zhejiang, China
dabao.wang@monash.edu

Siwei Wu
Zhejiang University
Hangzhou, Zhejiang, China
wusw1020@zju.edu.cn

Ziling Lin
Zhejiang University
Hangzhou, Zhejiang, China
linziling@zju.edu.cn

Lei Wu†
Zhejiang University
Hangzhou, Zhejiang, China
lei_wu@zju.edu.cn

Xingliang Yuan
Monash University
Melbourne, Victoria, Australia
xingliang.yuan@monash.edu

Yajin Zhou
Zhejiang University
Hangzhou, Zhejiang, China
yajin_zhou@zju.edu.cn

Haoyu Wang
Beijing University of Posts and Telecommunications
Beijing, China
haoyuwang@bupt.edu.cn

Kui Ren
Zhejiang University
Hangzhou, Zhejiang, China
kuiren@zju.edu.cn

ABSTRACT

Flash Loan, as an emerging service in the decentralized finance ecosystem, allows traders to request a non-collateral loan as long as the debt is repaid within the transaction. While providing convenience, it brings considerable challenges that Flash Loan allows speculative traders to leverage vulnerability of deployed protocols with vast capital and few risks and responsibilities. Most recently, attackers have gained over $\$15M$ profits from Eminence Finance [53] via exploiting Flash Loans to repeatedly swap tokens (i.e., EMN and DAI).

To be aware of foxy actions, we should understand what is the behavior running with the Flash Loan by traders. In this work, we propose `ThunderStorm`, a 3-phase transaction-based analysis framework, to systematically study Flash Loan on the Ethereum. Specifically, `ThunderStorm` first identifies Flash Loan transactions by applying observed transaction patterns, and then understands the semantics of the transactions based on *primitive* behaviors, and finally recovers the intentions of transactions according to *advanced* behaviors. To perform the evaluation, we apply `ThunderStorm` to existing transactions and investigate 11 well-known platforms. As the result,22, 244 transactions are determined to launch Flash Loan(s), and those Flash Loan transactions are further classified into 7 categories. Lastly, the measurement of financial behaviors based on Flash Loans is present to help further understand and explore the speculative usage of Flash Loan. The evaluation results demonstrate the capability of the proposed system.

KEYWORDS

Blockchain, Flash Loan, DeFi, Measurement

1 INTRODUCTION

Decentralized finance, aka DeFi, has drawn much attention in recent years. Up to 20th Oct 2020, the total value locked [1] of *DeFi* has reached 11 billion USD [18]. The popularity of *DeFi* is partially due to Flash Loan (i.e., non-collateral loan), which is impractical in the traditional centralized finance system.

However, the introduction of Flash Loan is a double-edged sword. On the one hand, it does bring in convenience [45] and facilitate the prosperity of *DeFi*. Traders without much capital can launch arbitrage, liquidation and asset swapping with Flash Loan. For instance, when traders discover a considerable price difference among tokens between decentralized exchanges (DEXes), Flash Loan can "generously" lend traders a considerable amount of capital to maximize profits and require them to repay at the end.

On the other hand, Flash Loan may raise risks [22] [21] to *DeFi*. With a Flash Loan, users can launch actions such as exchange, lending and borrowing, with a vast amount of assets that they do not have. In early 2020, two infamous incidents [22] [21] also cause a huge loss to bZx [9] (A lending & borrowing platform which also provides margin trading.). They take the advantage of the Flash Loan and manipulate the market price to make considerable profits of 829.5 thousand USDs and 1.1 million USDs, respectively [44]. Most recently, a trader borrowed 15M DAI [39] in a Flash Loan to gain over $\$15M$ through repeatedly swapping tokens on the EMN [52] pool.

As such, there is an urgent need to demystify the Flash Loan ecosystem, and understand the impact of potential security threats. Otherwise, it is impossible to provide effective mitigations without a comprehensive understanding. Unfortunately, few studies have been proposed to serve this purpose. Specifically, previous studies mainly focused on profit optimization [16, 44] and oracles [37] used in DEXes. To the best of our knowledge, none of them systematically demystified Flash Loan and its applications in *DeFi* ecosystem.

*Also with Monash University.
†Corresponding author

[1] Aka TVL, a standard to measure the total worth of the collateral deposited by users.

Namely, we still lack a comprehensive understanding of Flash Loan, especially the potential security impacts to the *DeFi* ecosystem.

Our approach. In this paper, we take the first step to systematically study Flash Loan in a comprehensive way. To this end, we propose a transaction-based analysis framework named `ThunderStorm` to demystify Flash Loan by measuring all existing transactions. `ThunderStorm` is composed of three components, including FLash-Loan Identifier, Primitive Classifier and Advanced Classifier, which provide a 3-phase filtering to produce three classes of transactions step by step. These classes of transactions will facilitate revealing the characteristic of Flash Loan.

Specifically, to support the analysis, we first collect and investigate 11 representative platforms to extract function/event signatures to feed into `ThunderStorm`. After that, with the help of collected patterns, `ThunderStorm` is capable of analyzing the existing transactions. Specifically, in the first phase, FLash-Loan Identifier locates all Flash Loan transactions until 10th Oct 2020 (Section 5.2). Then, in the second phase, Primitive Classifier groups these transactions into four primitives based on the behaviors acted within Flash Loan. Next, in the third phase, Advanced Classifier further categorizes four groups of transactions gained in the second phase into three advanced behaviors to reflect the intention of using the Flash Loan (Section 5.3). Last, `ThunderStorm` measures each class of transactions and presents their distribution and intersection to understand the frequency of each behavior utilized by users. We further articulate the challenges to deeply analyze advanced behaviors of Flash Loan transactions (Section 6).

Results. We have applied the proposed approach to analyze 4 representative Flash Loan providers, including *Aave* [4], *bZx* [9], *dYdX* [19] and *UniswapV2* [47]. For transactions of Flash Loan identified in the first phase, 22, 244 transactions were filtered from total 863, 504, 142 transactions mined until 10th Oct 2020. Among them, we discovered that over 60% of Flash Loan transactions were triggered by only 3.5% of borrowers. Lately, we conducted a behavior-based analysis on all filtered Flash Loan transactions and classified them into total 7 groups with primitives and advanced behaviors. Totally, 2, 331 transactions were collected. Furthermore, we concluded 3 challenges, i.e., 1) *How to collect historical information*; and 2) *How to interpret extracted information with meaningless parameter names*; and 3) *How to summarize comprehensive arbitrage behaviors to understand the behavior launched by users.*

Contributions. This paper provides the following main contributions:

- To the best of our knowledge, this paper is the first systematic study to understand Flash Loan. We propose a three-phase analysis framework to serve the need.
- We conduct full-chain measurements on financial behaviors launched with the Flash Loan in DeFi ecosystem. As far as we know, this is the first work to give a measurement for users' movements behind the Flash Loan based on real-world data.
- We analyze the distribution of the aforementioned behaviors, and exhibit the challenges that hinder us to further interpret the behavior with extracted information.

The rest of the paper is arranged as follows. Section 2 introduces the background of some concepts on Ehtereum and primitive behaviors on DeFi. Section 4 presents the workflow of `ThunderStorm` in details. Section 5 discusses the distribution of filtered results and how `ThunderStorm` help us to understand speculative usage of Flash Loan in the real world. Section 6 shows the identified challenges that hinder users from understanding the behavior behind Flash Loan. The related work is exhibited in Section 7. Finally, we conclude the paper in Section 8.

2 BACKGROUND

The introduction of the blockchain technique [42] has changed the financial ecology in the world. Especially with the invention of Ethereum [48], there has been a wave of developing the decentralized application (DApp). Smart contracts, as the basis of DApps, enable a transparent environment and become an essential component for the development of DeFi.

2.1 Common concepts on Ethereum

In order to make this work easy to understand, We first introduce a few common concepts on Ethereum.

Account: Ethereum is an account-centric blockchain system. There are two types of accounts: External Owned Account(EOA) and smart contract account (smart contract in short). The main difference between them is that EOAs are controlled by their private keys and smart contracts are controlled by their codes. Basically, an EOA is created with the generation of the public and private key pair, and a smart contract is always created by an EOA or another smart contract. Both EOAs and smart contracts are identified by their addresses, like `0x16431837a35b5469675b2ba5d9b7575d25b721c3`.

Digital currency There are two types of digital currencies in Ethereum, Ether and ERC20 token. Ether is supported natively, and ERC20 tokens are supported by smart contracts. Once a smart contract implements the interfaces of ERC20 token standard [1], then the smart contract can act as an ERC20 token. ERC20 tokens can only be transferred by invoking two ERC20 token standard functions: *transfer* and *transferFrom*, which is leveraged to track the flow of ERC20 tokens in the following.

Transaction: All actions on Ethereum are based on transactions. A transaction may have three purposes: transferring Ether, invoking a function of a smart contract and deploying a smart contract. Transactions are normally initiated from EOAs, but a transaction invoking a smart contract may trigger more transactions that are initiated from the smart contract, which depends on the smart contract's code. In order to distinguish them, we always refer the former as external transaction and the latter as internal transaction. The word "transaction" written individually in the remaining of the paper indicates the collection of an external transaction and internal transactions triggered by it.

Function/event: The function of smart contract is identified by the function signature, which is the first four bytes of the hash value (SHA3) of the function name with parenthesized list of parameter types. If a user sets a function signature in front of the call data of a transaction, then the corresponding function of the callee smart contract will be invoked. Smart contracts' developers usually leverage event to record critical information. For example,

ERC20 token standard specifies an event *Transfer* to record the spender, receiver and amount for a ERC20 token transfer. Similarly, an event is identified by the hash value (SHA3) of the event name with parenthesized list of parameter types. When an event is triggered, a log with event hash is recorded in Ethereum. In table 1, we take advantage of functions' signature and events' hash to identify various behaviors.

2.2 Finance Behaviors in *DeFi*

In Ethereum, DeFi is formed with a group of open-source protocols deployed as smart contracts. Compared to the traditional centralized finance system, decentralized finance is a transparent and permissionless finance ecosystem without relying on intermediaries such as banks.

Flash Loan. To request a loan in DeFi platforms, the borrower is normally required to deposit self-owned collaterals (i.e., digital cash or tokens). However, with the state reverting feature of Ethereum, a new service called *flash loan* is developed to enable a non-collateral borrowing service [44]. The flash loan can provide users a considerable amount, which is limited by the total locked value in the pool, of asset, as long as borrowed assets could be repaid within internal transactions triggered by the flash loan service. To our best knowledge, there are four platforms [4] [9] [19] [47] supporting flash loans with or without a certain percentage of the trading fee.

With the development of the flash loan service, two hacks [21] [22] on *15th* and *18th Feb 2020* caused a serious capital loss via leveraging the flash loan service provided by *dYdX* [19] and *bZx* [9], respectively. The attacker only spent a small amount of transaction fees to gain a considerable amount of profits.

Decentralized Exchange (DEX). To exchange two types of crypto assets in the decentralized circumstance, two exchange modes (LOB & AMM) are regularly leveraged by known DEX platforms. *Limit order book* (LOB) DEXes such as MakerDao [40], match a pair of buy and sell orders to perform the exchange for different types of crypto-assets with a compatible price agreed by the buyer and seller. As one of the most impactful innovations in *DeFi*, *Automated Market Maker* (AMM) DEXes like Uniswap [47] and Balancer [6] consist of various liquidity pools supported by liquidity providers who are normally required to deposit two different tokens for liquidity equilibrium. Different from LOB, AMM DEXes allow traders to exchange their crypto-assets with high flexibility. However, a considerable slippage could happen in Constant Function Market Maker (CFMM) DEXes, which are the most common class of AMMs, if there exists a considerable amount of exchange in a small liquidity pool.

Lending & Borrowing. As the replacement of the bank in *DeFi*, lending platforms share interests for depositors locking their capital in the liquidity pool and also provide a collateral loan for borrowers. To keep the balance of the loss, liquidation is applied once the cost of the borrowed out money is slipping.

Margin Trade. Margin trade is one of the most common financial derivatives. It is a risky behavior for traders to launch profit making. Moreover, the buyer normally plays it with a leverage to amplify the capital for more benefits, however, it speeds up the loss of their collateral as well. On 15 Feb 2020, a trader launches a margin trade with the vast capital borrowed from flash loan. This action manipulates the market price and creates a considerable profit-making opportunity.

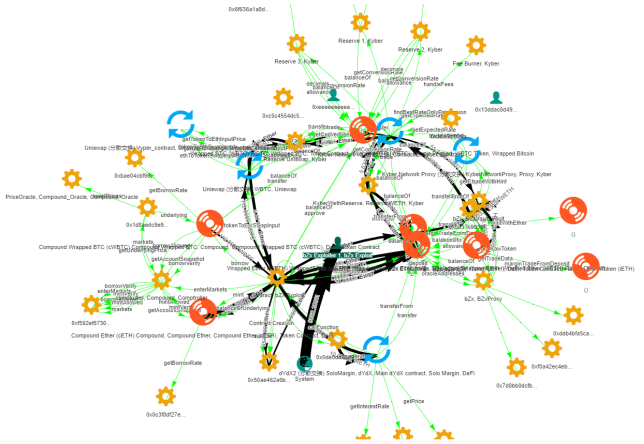


Figure 1: Invocation graph of the *bZx* hack in Bloxy [7]

Liquidation. The lending & borrowing, and margin trade platforms normally require traders to deposit more collateral than the borrowed assets with a certain ratio. To prevent the potential loss caused by price drop of traders' deposited collaterals, liquidation will be triggered. Platforms allow liquidators to launch auctions on trader's collateral if the boundary collateralization ratio(*collateral value*/*debt value*) is reached. As the consequence, traders could have a considerable loss (13% punishment applied in MakerDAO platform for CDP.) on their collateral. In contrast, the platform provides a discount and encourages liquidators to buy all liquidable collaterals. Liquidataion could happen everyday due to the price fluctuation in cryptocurrency market. On 12th March 2020, due to the large-scale turmoil in global financial market, the price of bitcoin is affected and dropping to the half or its original price as well as ether plunges dramatically too. This considerable drop causes traders' collateralization ratio falls below its minimum boundary as well as vast liquidations are triggered. Overall, exceeding 23M USD debt is liquidated on this single day. 3994 liquidations were triggered in MakerDAO and over 5M and 550K USD worth of crypto assets were liquidated on Compound and Aave, respectively.

3 A MOTIVATION EXAMPLE

Here, we use a real accident as the motivating example to lead the application of Flash Loan and demonstrate the difficulty and complexity to understand the whole picture. On February 15, 2020, an accident involving dYdX [19], bZx [9], Compound [14] and Uniswap [47] [2] made roughly $\$335,880$ [2], which known as bZx Hack. Ethereum analyst usually use Bloxy [7] to help analyze transactions. However, the transaction [21] in this accident contains a lot of internal transactions, which makes deeply understanding this accident difficult. As shown in Figure 1, the invocation graph provided by Bloxy is too complicated to identify behaviors in this accident.

[2]Kyber is a DEX aggregator, and it chose Uniswap as DEX in this attack. Therefore, we removed Kyber for simplicity.

We get the following two observations from the above accident. First, the huge initial capital is an essential prerequisite for this accident, and Flash Loan service can help users meet this prerequisite. Therefore, clarifying all applications of Flash Loan is an intuitive idea. Second, a *DeFi* platform may contain dozens of smart contracts with lots of interactions (with other *DeFi* platforms), which make *DeFi*-related transactions too complicated to understand. As Figure 1 shows, transaction involving *DeFi* platform is difficult to analyze, which motivates us to propose a better approach to help to identify and analyze these *DeFi*-related (or Flash Loan-related) behaviors.

4 METHODOLOGY

4.1 Overview

The purpose of our work is to understand the Flash Loan and its applications in Defi ecosystem. Without this knowledge, it is hard to understand the attacks that have occurred and propose the corresponding defenses. However, due to the large number of transactions in Ethereum and multiple smart contracts involved, our work must solve the following three challenges.

- First, we need to filter the transactions that are related Flash Loan efficiently, from billions of transactions in Ethereum and hundreds of smart contracts involved.
- Second, we need to quickly understand the semantics of the transactions and their primitives, e.g., performing exchanges, and margin trading.
- Third, we need to further understand the high-level intentions of the advanced behaviors involved in the Flash Loan related transactions, e.g., arbitrage and swapping.

Accordingly, we propose a three-phase solution to address the previous challenges.

- First, to filter transactions, we first define the *transaction patterns* used in the Flash Loan. The pattern includes transaction events, single function invocation or the chain of multiple function invocations (or transaction events) between smart contracts. Note that, we need to define the patterns for each platform that provides the Flash Loan service.
- Second, we leverage the transaction pattern to understand the semantics of the transaction. This provides us to construct four *primitives* used in DeFi applications, including exchange, lending and borrowing, margin trading and liquidation. For instance, if the `Borrow` function of the smart contract of the *AAVE* is invoked, then we know that the lending and borrowing behavior has occurred.
- Third, we understand the intentions of the transactions by the combination of the recovered primitives.

We propose a three-phase framework named `ThunderStorm` to perform the analysis. Figure 2 depicts the workflow of `ThunderStorm`, which consists of 3 major components, i.e., FLash-Loan Identifier, Primitive Classifier and Advanced Classifier. Each aims to solve one of the previous challenge. We will elaborate on them in the following sections.

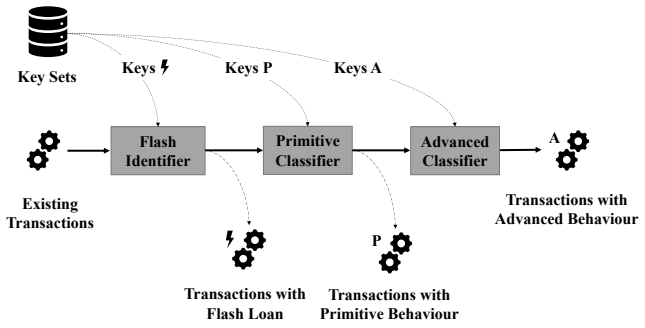


Figure 2: The workflow of `ThunderStorm`.

Primitive Pattern includes *Exchanging*, *Lending&Borrowing*, *Margin Trading* and *Liquidation*; **Advanced Pattern** includes *Arbitrage*, *Anti-Liquidation* and *Swapping*

4.2 Flash-Loan Identifier

Our approach uses transaction patterns to identify Flash Loan related transactions and classify the primitives. In our work, a transaction pattern could consist of the transaction event (that a specific event has occurred), the invocation of a function (through an internal transaction) and the chain of the invocation of functions between smart contracts.

However, unlike the ERC20 token [1], there is no standard for a DeFi application to use the standardized function names to implement the pre-defined functionality. Hence, we manually studied the popular DeFi platforms on *defiprime* [17], and constructed the transaction patterns.

Table 1 summarizes the platforms, and corresponding events and functions that are used to identify their provided services. For example, *Aave* implements a public function named *flashloan* to allow users to utilize its Flash Loan service. Thus when *flashLoan* is successfully called, the event *FlashLoan* will be triggered to record related information. We locate behaviors using the Flash Loan of *Aave* via the function signature of *flashLoan* and event hash of *FlashLoan*.

In the following, we will first elaborate on existing Flash Loan providers and the patterns to filter related transactions.

4.2.1 Determine Flash Loan Providers. Through investigating some sources, including the famous web source [17, 18] and open source code, platforms, i.e., *Aave* , *bZx*, *dYdX* and *UniswapV2* [3] are determined as Flash Loan providers. In this section, we give an introduction of each platform and describe how they provide Flash Loan with fees.

- ***Aave*** As the second large lending&borrowing platform in *DeFi*, up to date, *Aave* has over $1.12B in total value locked before Oct 2020 [18]. As the first platform officially providing the Flash Loan for users, *Aave* offers 17 different types of ctypto-assets including DAI, BAT, ETH and etc. To use Flash Loan in *Aave*, the platform charges 0.25% of the borrowed asset as a fee from users.

[3] Only *UniswapV2* provides Flash Loan service in Uniswap [47]

Table 1: Function signature or event hash of platforms

Flashloan				
Platform	**Function Name**	**Signature**	**Event Name**	**Event Hash**
AAVE	*flashLoan*	0x5cffe9de	*FlashLoan*	0x5b8f46461c1dd69fb968f1a003acee221ea3e19540e350233b612ddb43433b55
bZx	*flashBorrowToken*	0x66fa576f	-	-
Uniswap V2	*swap*	0x022c0d9f	*PairCreated*	0x0d3648bd0f6ba80134a33ba9275ac585d9d315f0ad8355cddefde31afa28d0e9
			Sawp	0xd78ad95fa46c994b6551d0da85fc275fe613ce37657fb8d5e3d130840159d822
dYdX	-	-	*LogOperate*	0x91b01baeee3a24b590d112613814d86801005c7ef9353e7fc1eaeaf33ccf83b0
			LogWithdraw	0xbc83c08f0b269b1726990c8348ffdf1ae1696244a14868d766e542a2f18cd7d4
			LogCall	0xab38cdc4a831ebe6542bf277d36b65dbc5c66a4d03ec6cf56ac38de05dc30098
			LogDeposit	0x2bad8bc95088af2c247b30fa2b2e6a0886f88625e0945cd3051008e0e270198f

Exchange				
Platform	**Function Name**	**Signature**	**Event Name**	**Hash**
Uniswap V1	-	-	*NewExchange*	0x9d42cb017eb05bd8944ab536a8b35bc68085931dd5f4356489801453923953f9
			TokenPurchase	0xcd60aa75dea3072fbc07ae6d7d856b5dc5f4eee88854f5b4abf7b680ef8bc50f
			ETHPurchase	0x7f4091b46c33e918a0f3aa42307641d17bb67029427a5369e54b353984238705
Balancer	-	-	*LOG_SWAP*	0x908fb5ee8f16c6bc9bc3690973819f32a4d4b10188134543c88706e0e1d43378
1.inch	*swap*	0xf88309d7	*Swapped*	0xe2cee3f6836059820b673943853afebd9b3026125dab0d774284e6f28a4855be
Synthetix	-	-	*Exchange*	0xdb1741ffc6844b04a9284bb6337fb0ccfe543a493ef0ac8e725242201e93d4bd
curveFi	-	-	*TokenExchange*	0x8b3e96f2b889fa771c53c981b40daf005f63f637f1869f707052d15a3dd97140
Kyber	-	-	*ExecuteTrade*	0x1849bd6a030a1bca28b83437fd3de96f3d27a5d172fa7e9c78e7b61468928a39
			KyberTrade	0xd30ca399cb43507ecec6a629a35cf45eb98cda550c27696dcb0d8c4a3873ce6c

Lending & Borrowing				
Platform	**Function Name**	**Signature**	**Event Name**	**Hash**
AAVE	-	-	*Borrow*	0x1e77446728e5558aa1b7e81e0cdab9cc1b075ba893b740600c76a315c2caa553
			Repay	0xb718f0b14f03d8c3adf35b15e3da52421b042ac879e5a689011a8b1e0036773d
			Deposit	0xc12c57b1c73a2c3a2ea4613e9476abb3d8d146857aab7329e24243fb59710c82
			RedeemUnderlying	0x9c4ed599cd8555b9c1e8cd7643240d7d71eb76b792948c49fcb4d411f7b6b3c6
bZx	-	-	*Borrow*	0x86e15dd78cd784ab7788bcf5b96b9395e86030e048e5faedcfe752c700f6157e
			Repay	0x85dfc0033a3e5b3b9b3151bd779c1f9b855d66b83ff5bb79283b68d82e8e5b73
			Mint	0xb4c03061fb5b7fed76389d5af8f2e0ddb09f8c70d1333abbb62582835e10accb
			Burn	0x743033787f4738ff4d6a7225ce2bd0977ee5f86b91a902a58f5e4d0b297b4644
Compound	-	-	*Borrow*	0x13ed6866d4e1ee6da46f845c46d7e54120883d75c5ea9a2dacc1c4ca8984ab80
			RepayBorrow	0x1a2a22cb034d26d1854bdc6666a5b91fe25efbbb5dcad3b0355478d6f5c362a1
			Mint	0x4c209b5fc8ad50758f13e2e1088ba56a560dff690a1c6fef26394f4c03821c4f
			Redeem	0xe5b754fb1abb7f01b499791d0b820ae3b6af3424ac1c59768edb53f4ec31a929
Maker DAO	*frob*	0x76088703	*anonymous*	0x760887030000000000000000000000000000000000000000000000000000000000000000

Margin Trade				
Platform	**Function Name**	**Signature**	**Event Name**	**Hash**
bZx	*MintWithEther*	0x4e07008d 0xd24f22a9	*Mint*	0x458f5fa412d0f69b08dd84872b0215675cc67bc1d5b6fd93300a1c3878b86196
	MintWithToken	0x39039497 0xf5acf904		

Liquidation				
Platform	**Function Name**	**Signature**	**Event Name**	**Hash**
AAVE	-	-	*LiquidationCall*	0x56864757fd5b1fc9f38f5f3a981cd8ae512ce41b902cf73fc506ee369c6bc237
Compound	-	-	*LiquidateBorrow*	0x196893d3172b176a2d1d257008db8d8d97c8d19c485b21a653c309df6503262f
dYdX	-	-	*LogLiquidate*	0x1b9e65b359b871d74b1af1fc8b13b11635bfb097c4631b091eb762fda7e67dc7
opyn	-	-	*Liquidate*	0xcab8e1abb9f8235c6db895cf185336dc9461aecf477b98c1be83687ee549e66a

- ***dYdX*** *dYdX* is a lending and borrowing platform with over $24M total value locked up to date. Apart from lending and borrowing service, it provides the margin trading service as well. As for the Flash Loan service, there is no official publication for Flash Loan in *dYdX*. However, *dYdX* allows users to perform Flash Loan logic, which is to call the function *'withdraw'* before *'deposit'*, by starting with provided *'operate'* function. In addition, there is no extract fee charged except the basic transaction gas.
- ***bZx*** Similar to *dYdX*, *bZx* provides both lending and borrowing and margin trading, but with less total value locked (around

Algorithm 1: The Algorithm to Identify Flash Loan Transactions

```
ExtractInfo (t, p)
    inputs : Flash Loan transaction t; Identifying pattern p;
    output: Expecting information info
    info ← ∅;
    foreach para ∈ p.Parameters do
        if Identified by Event from p then
            info[para] ← Event[para] in t;
        else
            info[para] ← Function[para] in t;
    foreach Internal transaction it ∈ t do
        if it executes flash_loan_borrow then
            info[IntStart] ← it.index;
        else if it executes flash_loan_repay then
            info[IntEnd] ← it.index;
            break;
    return info;
Identifying (P, T)
    inputs : Collected patterns P for Flash Loan; Collected
             existing transactions T;
    output: Flash loan transactions fT;
    fT ← ∅;
    foreach t ∈ T do
        foreach p ∈ P do
            info ← ∅;
            if Pattern p is identified in t then
                info ← ExtractInfo(t, p);
                fT[t] ← info;
                break;
    return fT;
```

$250K). As an ERC20 token based protocol, *bZx* launches different services with different tokens: BZXToken, iToken, and pToken [9]. As for its Flash Loan service, *bZx* does not declare the Flash Loan officially and it requires no fees except basic transaction gas.

- ***UniswapV2*** As one of the most well-known DEX, *Uniswap* has the highest total value locked (over $2.7B) among all DEXes. Recently, the latest protocol *UniswapV2* is published by the community and a new feature called flash swap is introduced. This feature inherits the property of Flash Loan which allows users to get crypto-assets in advance and repay them after a series of actions. In terms of the fee, compared to the aforementioned Flash Loan providers, it charges the highest percentage(0.3%) of fees based on users' borrowed asset.

4.2.2 Identify Flash Loan Transactions. To effectively identify Flash Loan, we use the patterns used by each Flash Loan provider. Moreover, we precisely present the filtering logic to identify Flash Loan among aggregated transactions. Furthermore, we structure the general identifying process in function *Identifying* presented in Algorithm 1.

Through running the function *Identifying*, it returns a set of Flash Loan transactions fT with input of pre-collected patterns P and existing transactions (up to 10th Oct 2020) T. Specifically, we firstly initiate an empty set fT, then we iterate each pattern p of P for each transaction t of T. For each pair of *(p, t)*, once we can identify the pattern p in the transaction t, function *ExtractInfo(t,p)* which is revealed in the next subsection, will be triggered to collect information of Flash Loan. Furthermore, the identified transaction t and corresponding information *info* will be appended to the set fT.

For each Flash Loan provider, the logic applied in the condition of `if` loop is different. We will elaborate for each provider in the following.

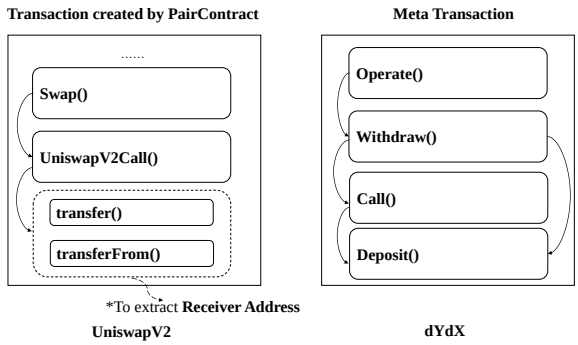
***Aave*:** Specifically, *Aave* exposes an external function called `flashloan` [4] in the smart contract *AAVELendingPool* for users to utilize the Flash Loan service. Moreover, once the Flash Loan is executed successfully, a corresponding event will be emitted so that we can further confirm the existence of Flash Loan in a transaction. To identify Flash Loan of *Aave* in a transaction, we firstly search the hash value of the emitted event among all events of current transaction. Then we check the "from" address with the contract address [5] of *AAVELendingPool*. If both conditions, i.e., event is found and the "from" address is confirmed, this transaction definitely contains Flash Loan from *Aave*.

***bZx*:** Similar with *Aave*, locating the transactions including Flash Loan requires an identification of the invocation of borrowing any type of *iToken* [6] from *bZx*. With the function signature of *flashBorrowToken* and all iToken's addresses, once the function *flashBorrowToken* [7] in *iToken* is invoked, then this transaction must include Flash Loan supported by *bZx*.

***UniswapV2*:** As aforementioned, Flash Loan is inherited as the *flash swap* feature in *UniswapV2*. However, based on the protocol of *UniswapV2*, a normal crypto-assets swap and a flash swap are both operated via invoking a same function *swap*. To differentiate them, we check the existence of the *payback* action, which is simply the *transfer* or *transferFrom* function sending the token back to the contract operating *swap* function.

First, since the *swap* function is only invoked in contract *UniswapV2Pair* created by *UniswapV2Factory* [8], we collected all pair contracts via identifying the address of *UniswapV2Factory* associated with the hash value of the event PairCreated. As the result, we get a group of filtered addresses for the next round of filtering. Second, with the help of the function signature of *swap*, the transaction triggered by this function could be located easily. As shown in Figure 3, the function *uniswapV2Call* is invoked in *swap* to launch the payback action. Moreover, to confirm the existence of the payback action, three conditions should be fulfilled, including 1) existing call-data in the function *uniswapV2Call*; 2) all internal transactions triggered by the calling data must present a *transfer transferFrom* function; 3) in the *transfer* or *transferFrom* function,

[4] flashLoan(address _receiver, address _reserve, uint256 _amount, bytes calldata _params)
[5] 0x398ec7346dcd622edc5ae82352f02be94c62d119
[6] They are interest accumulating tokens that continuously go up in value as you hold them [10]
[7] flashBorrowToken(uint256 borrowAmount,address borrower,address target,string signature,bytes data)
[8] The contract address is 0x5c69bee701ef814a2b6a3edd4b1652cb9cc5aa6f.



*iff the *receiver address* is equal to *PairContract address*, then it is considered as "flash swap".

Figure 3: Flash Loan in UniswapV2 and dYdX

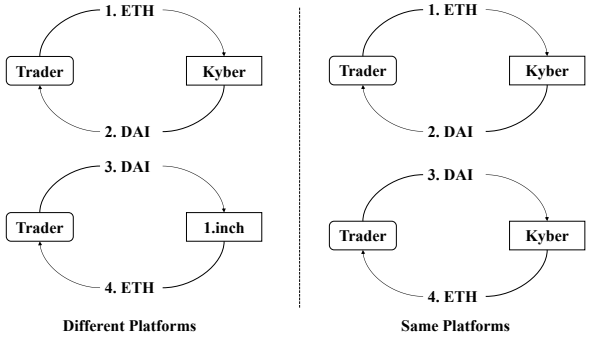


Figure 4: The workflow of Arbitrage.

the receiver must be the address of current pair contract which triggered the *swap* function.

Once these three conditions are fulfilled, the flash swap (i.e., Flash Loan in *UniswapV2*) can be confirmed in the transaction.

***dYdX*:** Flash Loan must be completed in a single transaction in *dYdX*. As aforementioned, Flash Loan in *dYdX* is constructed by starting calling the *operate* function. Normally, a transaction is created by a function call. In *dYdX*, it allows the combination of functions to create one meta transaction. Particularly, a meta transaction is constructed with functions: *Operate*, *Withdraw*, *callFunction* [9], and *Deposit* in order. In Figure 3, the basic structure of a meta transaction for Flash Loan is present and we use function `Call` to replace the function *callFunction*.

Furthermore, for each function mentioned above, they all have a corresponding event and these events, which are *LogOperate*, *LogWithdraw*, *LogCall*, and *LogDeposit*, are defined as patterns and specified in Table 1. Therefore, as long as we can identify ordered events based on either of the following two invocation flows, then the transaction certainly has Flash Loan.

- `LogOperate` ⟶ `LogCall` ⟶ `LogWithdraw` ⟶ `LogDeposit`
- `LogOperate` ⟶ `LogWithdraw` ⟶ `LogDeposit`

4.2.3 Extract the Position information in Internal Transactions (Information Extracting). To better understand actions associated with the Flash Loan, extra information is also needed.

In Algorithm 1, once the Flash Loan is confirmed in function *Identifying*, the function *ExtractInfo(p, t)* is triggered instantly to extract required information listed in Table 2 for Flash Loan. For details, *ExtractInfo(p, t)* returns the expected information. More specifically, first of all, all parameters mentioned in functions used to identify Flash Loan will be aggregated. Apart from the parameter, the index of the start and the end of internal transactions covered in the Flash Loan are collected. These two indexes are used to limit our further analysis (Section 4.3) within the transactions that are related with Flash Loan.

[9] `callFunction(address sender,Account.Info memory account,bytes memory data)public`

4.3 Primitive Classifier

After filtering Flash Loan related transactions, our next step is to recover the semantics of the transactions to four *primitive*s. A *primitive* here is used to describe the most straightforward services provided in *DeFi*, including decentralized exchange (DEX), lending and borrowing, margin trading and liquidation. These primitives are the foundations for the next step to classify and understand the advanced behaviors.

Note that, in this step, we use the identified Flash Loan transactions in the previous step as the input, since our purpose is to understand Flash Loan related behaviors. The basic idea is still using the patterns defined for each primitive to filter the transactions. The method is similar with the previous step, but with different patterns used. Table 1 shows the patterns for each primitive.

4.4 Advanced Behavior Classifier

Advanced Classifier aims to reveal the high-level action from traders' initial purposes and intention like arbitrage, preventing positions from liquidation and swapping. This phase takes transactions returned by Primitive Classifier as the input. We take different strategies to identify them.

4.4.1 Arbitrage. Generally speaking, the opportunity of arbitrages are due to price and interest rate fluctuation of assets. The *DeFi* normally reacts slower for events happening in the network than the real world market. Therefore, traders can take the advantage of the inefficiencies of the market to buy/deposit and sell/withdraw the asset across different platforms.

We analyze the arbitrage strategies with two key components, i.e., *price* and *interest rate*. For price arbitrage, since the price synchronization latency in *DeFi*, it allows traders to make gains via trading the same asset with price difference among different platforms. On the other hand, interest rate arbitrage normally happens in lending and borrowing platforms. Depositing capital in platforms providing higher interest rate could give users more benefits.

Here we mainly analyze the most common arbitrage, in which traders "smartly" leverage the price difference. Moreover, speculative traders might even manipulate the price leveraging the constant-value mechanism deployed by AMM DEXes [47], which

maintains a constant proportion of value in each asset of the portfolio. Arbitrage behavior transactions are identified based on the DEX transactions filtered at the previous phase.

As shown in Figure 4, we present two cases to describe the workflow of arbitrage identification. On the left, a trader swaps out DAI by providing ETH within Kyber [34]. Later on, the same trader launches another swap to replace ETH with DAI in 1*inch* [3] again. Therefore, in our strategy, we define the pattern of arbitrage by searching at least two trades launching with a same trader.

4.4.2 Anti-Liquidation. Liquidation happens nearly every day in *DeFi*. Through experiencing the black Thursday in early 2020, protecting existed collateral could not be underestimated by traders because of the considerable punishment. We collect three ways [45] which can prevent liquidations from happening. Furthermore, for the ease of understanding, we rename this category of actions as Anti-Liquidation. When a premonition of the price drop is encountered, traders can have three options listed below:

(1) Repaying all debts with the required fee to save the collateral. This option saves the trader from devaluation at once, but the loss is fixed as well.
(2) Depositing more assets into the platform to increase the collateralization ratio. This method gives the trader a chance to manage their loss or even revive. However, it might lead to a more serious loss if the price drop is continuing.
(3) Instead of completely unwinding the position, traders can partially payback their debt with their deposited collateral. This partially payback does not only protect user's collateral by increasing the collateralization ratio, traders can have collateral remaining in the pool.

In this work, we only focus on the anti-liquidation behavior of a well-known third-party platform, i.e., *DeFi Saver* [45]. *DeFi Saver*, which is known as *CDP Saver*, is originally an advance management platform dashboard for CDP in MakerDAO [40], as well as capital and portfolio in Compound [15]. It provides automation solutions including decreasing loan ratio to prevent users from liquidation. On 1st Oct 2020, *DeFi Saver* announced the adoption of *Aave* Flash Loan service is finally done, which means that *DeFi Saver* now can launch an instant saving for users' capital due to the price fluctuation. Moreover, compared to the punishment of liquidation, *DeFi Saver* only charge a few amounts of fee for users. To locate such anti-liquidation behavior launched by *DeFi Saver*, we can easily leverage its corresponding event identify in transactions.

4.4.3 Swapping. Through monitoring the price and timely swapping capitals might help users gain significant profit in *DeFi* because of its unpredictable and changeable market attributes. A low charged interest rate, a low bounded collateralization ratio or a better reward to the liquidity supplier can attract traders to launch such an action to refinance their capitals to gain the most profits. We combine three types of actions, i.e., collateral swapping, loan swapping and platform swapping, as swapping in our work. Among them, the collateral swapping changes the collateral types but borrows the same coin, while the loan swapping keeps the collateral with different assets borrowed out. As for the platform swapping, the trader closes a loan in one platform, draws out the collateral and opens a new vault in another platform. These actions require the traders to pay back the debts to go further. However, the loan borrowed by traders is normally used instantly. Instead of taking time to organize capital to swap, with the help of Flash Loan, traders can directly launch swapping.

All classified lending and borrowing transactions are used as the input for swapping identification. Moreover, in this work, we performed collateral swapping identification associated with the patterns collected in *MakerDAO* as well as loan swapping identification with the required pattern in *Compound* and *Aave*.

- **Collateral Swapping.** Achieving collateral swapping requires two compulsory actions: redeeming old collateral and opening a new loan. The basic idea of the behavior is to close the old loan and open a new loan. The asset borrowed from the flash loan can be either used to repay the debt to redeem the original collateral or to open a new loan. More specifically, the patterns required in the collateral swapping identification process with MakerDAO expresses two main actions: redeeming original collateral and depositing the new type of collateral. Once two actions are identified with the required pattern, two collateral asset types will be extracted. Then the collateral swapping will be finally confirmed in the flash loan transaction.
- **Loan Swapping.** Different from collateral swapping, there is no change needed for collateral to achieve such behaviors. The borrowed assets from the Flash Loan are used to repay the loan. Furthermore, with the original collateral, another type of loan will be opened. The classifying process is quite similar to the collateral swapping apart from the actions used to search. Specifically, two actions, i.e., repaying the loan back and borrowing a new loan, are constructed. On the other hand, the assets which pay back the old loan and the asset being borrowed should also be identical to further confirm the loan swapping behavior.
- **Platform Swapping.** Similar to the collateral swapping, an old loan must be close and a new vault will be opened. But these two actions happen in two platforms. Therefore the patterns of paying back the debt and drawing out the collateral in a platform, as well as depositing in another platform are checked to confirm such a behavior.

Table 2: Parameter Allocation for Primitive Behaviors .

Parameter Types	Flash Loan	Primitive Behaviors			
		Ex	LB	MT	Li
Service Provider★	✓	✓	✓	✓	✓
Runner★	✓	✓	✓	✓	✓
Receiver		✓	✓		✓
Asset In	✓	✓	✓	✓	
Asset Out	✓	✓	✓	✓	✓
Amount In	✓	✓	✓	✓	✓
Block Number	✓	✓	✓	✓	✓
Transaction Index	✓	✓	✓	✓	✓

★The *Service Provider* includes the provider of Flash Loan and other services. The *Runner* indicates a trader or a liquidator.

5 EVALUATION

In this section, we will provide an in-depth evaluation based on our proposed approach discussed in Section 4. Specifically, to facilitate the understanding of Flash Loan, we seek to answer the following research questions:

- **RQ1** How Flash Loan works with different platforms and how frequent of Flash Loan is used in each platform.
- **RQ2** How frequent behaviors are launching with Flash Loan and what their distribution is in the whole blockchain ledger.
- **RQ3** Can `ThunderStorm` help security analysts to understand the speculative usage of Flash Loan in the real world?

Finally, we will demonstrate the capability of our analysis by delving into the details of the real world events in Section 5.4.

5.1 Data Set

We collect total 863, 504, 142 existing transactions from Ethereum blockchain ledger with its state information, which include emitted events and invoked functions, until 10th Oct 2020.

5.2 Flash Loan Distribution

This section targets **RQ1**. Through running FLash-Loan Identifier on all existing transactions, 22, 244 transactions containing Flash Loan are identified. Moreover, Table 3 lists the number of Flash Loan invoked by users in each platform.

Table 3: Distribution of Flash Loan transactions.

Providers	# of Transactions	# of borrowers
Aave	6, 199	301
bZx	3	3
UniswapV2	2, 883	234
dYdX	13, 203	393
Total	22, 244*	908*

* As one transaction may include two Flash Loan, and it is possible for borrowers to use Flash Loan in different platforms. As a result, for each column, the sum of rows (except "Total") is more than the corresponding total number.

It can be found from the results that users leverage the Flash Loan in *dYdX* most frequently, as there are 13, 203 transactions which are over half of the total amount of Flash Loan transactions. Following up, 6, 199 Flash Loan transactions are found in *Aave*, and 2, 883 Flash Loan transactions are found in *UniswapV2*. Note that the number in *UniswapV2* could increase rapidly since its Flash Loan service is announced very recently compared to the one in *dYdX* and *Aave*. Another interesting founding is that although only 3 transactions are identified in *bZx*, the infamous arbitrage on 18 Feb 2020 [22] is covered within those transactions.

In Table 3, the number of borrowers is also presented. According to the results, the Flash Loan services in *Aave* and *dYdX* are more popular. Surprisingly, 60% of Flash Loan transactions are launched by only 3.5% of borrowers. More specifically, in *Aave*, the top 10 borrowers (out of 301) run nearly 70% of the Flash Loan transactions. We found that the main user of the *Aave* Flash Loan is *DeFi Saver* which takes 8 places among the top 10 borrowers. Moreover, the user who launches the second most times of Flash Loan is *Furucombo* platform [26] which combines all Kyber DApps to allow users to launch their arbitrage in between two DEXes: Uniswap and Kyber with their own-discovered arbitrage opportunities. In conclusion, this phenomenon reveals that Flash Loan is currently a new service which is vastly used by some large organizations, rather than individuals.

> **Findings #1:** *dYdX occupies the most (*13, 202*, around 60%) of Flash Loan transactions, while bZx creates the least (only 3). The proportions of Aave and UniswapV2 are 13% and 27%, respectively. Besides, the usage of Flash Loan is currently dominated by large organizations (3.5% of borrowers launch 60% transactions), rather than individuals.*

5.3 Behavior Distribution

This section targets **RQ2**. Specifically, to understand the behaviors, we use our proposed FLash-Loan Identifier to filter 22, 244 Flash Loan transactions from all existing ones in Ethereum. Through applying both Primitive Classifier and Advanced Classifier, those filtered transactions are classified into 7 behaviors including exchange, lending & borrowing, margin trade, liquidation, arbitrage, anti-liquidation, and swap.

Table 4: Existing Behaviors.

Behaviors		# of Transactions
Primitive	Exchange	22, 244
	Lending & Borrowing	7, 767
	Margin Trade	1
	Liquidation	164
	Total	22, 244
Advanced	Arbitrage	402
	Anti-Liquidation	1, 871
	Swapping*	101
	Total	2, 331

* There exists 55, 20 and 26 transactions performing collateral swapping, loan swapping and platform swapping respectively.

As shown in the Table 4, there are 22, 244 transactions identified by Primitive Classifier, including 22, 244, 7, 867 and 164 for exchange, lending & borrowing, and liquidation, respectively. Based on the result, we discovered that exchange, as the basic service, dominates the scope of usage in flash loans. For the margin trade, we found that only 1 transaction was conducted. After verifying this transaction, we found that it could be regarded as *price manipulation* [10]. This inactive behavior probably due to the leverage used therein, as a high leverage may increase the risk of collateral damage.

As for the 2, 331 transactions with advanced behaviors produced via running Advanced Classifier, arbitrage, anti-liquidation, and swapping are found in 402, 1, 871, and 101 transactions, respectively. Based on the results, anti-liquidation seems to be the most

[10] I.e., a speculative user can margin trade with leverages to manipulate the price in an AMM DEX to make an opportunity for arbitrage.

Table 5: Internal transaction classification of the *bZx* hack.

DeFi Behaviors	# Start Internal Transaction (index)	# End Internal Transaction (index)
Flash Loan in *dYdX*	2	188
Collateral Borrowing in Compound	21	46
Margin Trading in *bZx*	47	174
First Swapping in Uniswap	158	161
Second Swapping in Uniswap	176	180

demanding function in three advanced behaviors compared to arbitrage and swapping. Our investigation shows that the dramatic price fluctuation on 15th March 2020 is most possibly the reason because it causes a massive amount of liquidation.

Findings #2: *For primitive behaviors, exchange (*22, 244*, 100%) dominates the scope of usage in Flash Loan, and lending & borrowing (*7, 767*, around 35%) takes the second place. Liquidation (*164*) and margin trade (*1*) are far more behind. For advanced behaviors, anti-liquidation associates with the most (*1, 871*) transactions. Arbitrage and swapping occupy* 402 *and* 101*, respectively.*

5.4 Speculative Usage of Flash Loan in The Real World

This section focuses on **RQ3**. Specifically, *DeFi* ecosystem is still immature, with the new-born service Flash Loan, there exists some traders trying to gain themselves considerable profits via "smartly" leveraging the flash loan, such as infamous use cases [21] [22] [23] [24] leveraging Flash Loan. However, these cases usually cross multiple DeFi platforms, which make understanding these cases complicated. That is because they involved a lot of different contract invocation.

We take the *bZx* hack [2] introduced in Section 3 as an example to demonstrate that the proposed approach is capable of analyzing and understanding the speculative usage of Flash Loan. First, for each external transaction, `ThunderStorm` marks each internal transaction triggered by it in the order of execution (with indexes) . Then, `ThunderStorm` records the start and end indexes of the internal transaction for each behavior when identifying *DeFi* behaviors in Section 4.

As shown in Table 5, the internal transactions (or contract invocations) of the *bZx* hack are classified automatically according to the recognized behaviors. For example, Flash Loan in *dYdX* (the first row in the table) has 187 internal transactions (from index 2 to index 188), which means almost all actions (e.g., Margin Trading in *bZx* in the third row, from 47 to index 174) must be completed before paying back this Flash Loan. With that information, we only need to manually check the contract invocation between these *DeFi* behaviors, and the whole scope of the *bZx* hack can be easily captured. By doing so, `ThunderStorm` will help reduce the burden for security analysts.

Figure. 5 shows the attack details. In particular, the attacker launches the following five steps to complete this attack.

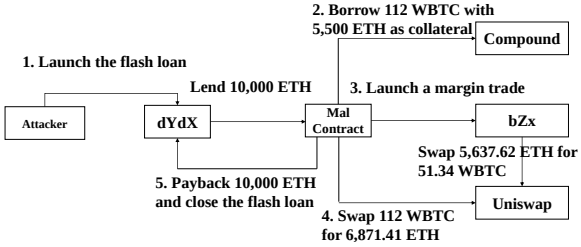


Figure 5: The details of bZx hack on February 15, 2020

(1) The attacker takes advantage of the Flash Loan service provided by *dYdX* to get 10, 000 ETH start-up capital, and sets the receiver as a malicious contract.
(2) The malicious contract then borrows 112 WBTC from Compound with 5, 500 ETH as collateral.
(3) The malicious contract uses the margin trade service of *bZx* to short ETH in favor of WBTC. In particular, it deposits 1, 300 ETH as margin, and then *dYdX* swaps the borrowed 5, 637.62 ETH for 51.34 WBTC in *Uniswap* [11]. This is the *critical* step, which essentially triples the WBTC price in *Uniswap*.
(4) The malicious contract swaps the borrowed 112 WBTC in step 2 for 6, 871.41 ETH.
(5) The malicious contract pays the 10, 000 ETH Flash Loan back to *dYdX*.

Until now, the attacker profits around 71 ETH, and if he repays the 112 WBTC loan to Compound with average market price [12] at that time, he will gain another roughly 1, 200 ETH [13]. Obviously, without `ThunderStorm`, it is not easy to recover the whole process of such a complicated hack.

Findings #3: *Based on the proposed approach, we have made a meaningful step towards understanding speculative usage of Flash Loan associated with complicated invocations and a large number of transactions.*

6 DISCUSSION

In this section, we elaborate on the limitations of our work. There exist several challenges hindering from a deep understanding of behavior based merely on Ethereum transactions.

Pattern Coverage. We tried our best to collect patterns, however, the completeness of the collected patterns cannot be absolutely guaranteed. Due to the rapid iteration and security threats faced by open source and pubic platforms, protocols based on the agreement of the community are updated quickly to protect users' locked capitals. However, due to such frequent updates, the pattern collection of historical smart contracts that are normally closed or destroyed becomes a challenge. Moreover, platforms only enable their development documentation with the latest version.

[11] Under the normal exchange rate, 5, 637.62 ETH can be exchanged for around 146.43 WBTC
[12] 1WBTC = 38.5ETH
[13] Collateral borrowing usually requires users to mortgage assets more valuable than borrowing

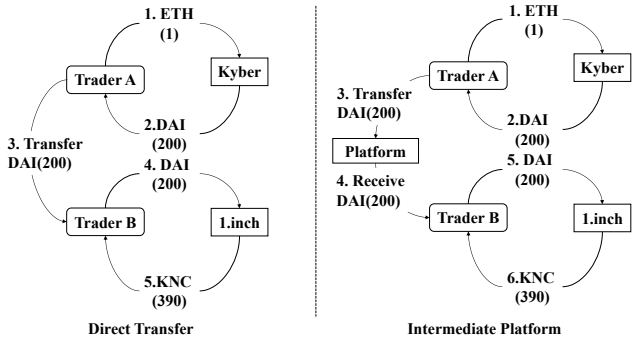


Figure 6: Challenges in Arbitrages.

Interpretation of Information. To fully understand the behaviors, it requires an adequate interpretation of extracted information. Most of the extracted information can be interpreted by the full name of the collected signature. However, to understand the type of trading assets being transferred between traders and platforms, collecting corresponding flags (addresses) is compulsory to automatically launch the filtering and classifying process on a large-scale of transactions. Moreover, for instance, the leverage amount of a margin trade in *bZx* cannot be revealed straightly from the parameters of the key function signature. This requires us to conduct a more specific study to nail this problem.

Variety of Arbitrage. As long as two trades with the same user are identified in a transaction, we confirm that is a price difference arbitrage. To further improve the understanding of such an arbitrage pattern, however, we meet some challenges.

- **Well-Connected Cash Flow.** Since we only consider one user in our pattern, this leaves a question on group trading, i.e., multiple addresses are involved for arbitrage with consensus. As shown in Figure 6, we exhibit two scenarios: 1) direct transfer; and 2) transfer through an intermediate platform such as the Lending & Borrowing platform between traders. To overcome such a challenge via transfer relationship between traders, one needs to construct a cash flow based on transfer functions fixed in the ERC20 token standard or general ether transfer function.
- **Profit Measurement.** Accurately measuring the profit made by an arbitrage for different input and output assets requires real-time prices in each block. It is not easy to calculate the price with only state data recorded in the Ethereum ledger. Based on a prior work [49] which maintains the state for each transaction in Ethereum, one can recover the state data of involved DEXes to calculate the exchange rate to ETH for each type of asset so that the profit can be estimated based on one asset. We leave it as our future work.

7 RELATED WORK

DeFi Security and Arbitrage. Kaihua et al. [44] investigate two existing exploits which happened on 15th and 18th Feb 2020, and present the details of how traders leverage the flash loan mechanism with the trick of price manipulation to gain profit. They also proposed a process to re-boost two exploits via optimized parameters. 2.37X and 1.73X of profits gained in their simulation for two exploits, respectively. Lewis et al. [29] leverage the flash loan to execute a governance attack [54] on MakerDAO [40]. Moreover, the proposed strategy leads to a theft of 0.5B USD and unlimited mining of DAIs. Bowen et al. [37] systematically investigate oracle designs of 4 *DeFi* platforms with open source code via comparing their price deviations, and exhibit their potential security vulnerabilities. Kamps et al. [32] aggregate the information from the existing pump and dump schemes among the classic economic, and propose a group of patterns with summarised criteria to identify potential pump and dump activities in crypto markets. Xu et al. [51] also conduct an investigation on 412 pump and dump activities to build a model that predicts the pump behavior for all assets exhibiting in DEXes by estimating its pump likelihood. Philip et al. [16] present the breadth of DEX arbitrage bots and their profit-making strategies which optimize users' network latency and pay a high transaction gas fee to win priority gas auctions (PGAs) so that their transaction can obtain priority ordering in the competition. Through the study, Daian et al. [16] highlights that bots' revenue far exceeds the Ethereum block reward and transaction fees, and with such high optimization fees, the blockchain consensus stability might be threatened. Eskandari et al. [20] also study the front-running issues across the top 25 most active decentralized applications (DApps) of Ethereum blockchain and exhibit the proposed solutions into useful categories.

Defi Monetary. Clark et al. [13] give a survey about 'stablecoin' of *DeFi* protocols and comparison among a list of cryptocurrencies like Bitcoin, Ether and etc. Furthermore, Pernice et al. [43] present a comprehensive taxonomy of cryptocurrency stabilization through combining their findings and studying classical monetary policy. Moin et al. [41] systematically explore existing stablecoins via decomposing their design into various component elements and introduce their strengths, drawbacks, and future directions. Lastly, Kolodner et al. [8] investigate Namecoin, which is the fork of Bitcoin, and empirically study its name services.

Smart Contract Security. Apart from the issues mentioned in *DeFi* ecosystem, potential or existing vulnerabilities of smart contracts, as the running base of *DeFi* services, could cause a considerable financial impact for *DeFi* as well. A group of surveys [35] [36] [5] [12] have soundly studied different aspects of the smart contract, especially in term of its vulnerabilities and security issues. In the following, we categorize the type of smart contract analysis into two classes. Static analysis, especially symbolic execution technique, has been used to examine smart contracts in different code levels: EVM bytecode [27] [33] [38], source code [31] [11] and intermediate representation [46] of smart contracts. On the other perspective, the fuzzing technique plays a vital role in dynamic analysis to detect the vulnerabilities of smart contracts. Different improved fuzzing techniques [30] [25] [50] or constructed fuzzing frameworks [28] are conducted to discover the vulnerability of smart contracts during run-time.

8 CONCLUSION

This paper takes the first step to systematically measure the financial application behind Flash Loan mechanism on the Ethereum.

With the non-collateral feature, the Flash Loan has been leveraged for advanced behaviors which match users' original purpose such as arbitrage, preventing from liquidation or collateral swap. In this work, we present 3-phase framework named `ThunderStorm` to identify each behavior within the Flash Loan transactions. In total, we collect and identify 22, 244 Flash Loan transactions, 22, 244 primitive behavior transactions, and 2, 374 advanced behavior transactions. To better understand the behaviors behind Flash Loan, we also extract the information for each behavior as well as the distribution. Finally, we use a real world case to demonstrate the capability of the proposed system.

REFERENCES

[1] 2015. ERC20 Token Standard. https://github.com/ethereum/EIPs/blob/master/EIPS/eip-20.md.

[2] 2020. bZx Hack Full Disclosure (With Detailed Profit Analysis). https://medium.com/@peckshield/bzx-hack-full-disclosure-with-detailed-profit-analysis-e6b1fa9b18fc.

[3] 1inch. Last Accessed: Oct. 2020. 1inch. 1inch.exchange.

[4] Aave. Last Accessed: Sep. 2020. Aave. aave.com.

[5] Nicola Atzei, Massimo Bartoletti, and Tiziana Cimoli. 2017. A survey of attacks on ethereum smart contracts (sok). In *International conference on principles of security and trust*. Springer, 164–186.

[6] Balancer. Last Accessed: Oct. 2020. Balancer Exchange. balancer.exchange.

[7] Bloxy. Last Accessed: Oct. 2020. Bloxy. https://bloxy.info/.

[8] Lorenz Breidenbach, Phil Daian, Florian Tramèr, and Ari Juels. 2018. Enter the hydra: Towards principled bug bounties and exploit-resistant smart contracts. In *27th {USENIX} Security Symposium ({USENIX} Security 18)*. 1335–1352.

[9] bZx. Last Accessed: Sep. 2020. bZx. bzx.network.

[10] bZx. Last Accessed: Sep. 2020. What are iTokens? bzx.network/itokens.

[11] Jialiang Chang, Bo Gao, Hao Xiao, Jun Sun, Yan Cai, and Zijiang Yang. 2019. sCompile: Critical path identification and analysis for smart contracts. In *International Conference on Formal Engineering Methods*. Springer, 286–304.

[12] Huashan Chen, Marcus Pendleton, Laurent Njilla, and Shouhuai Xu. 2020. A Survey on Ethereum Systems Security: Vulnerabilities, Attacks, and Defenses. *ACM Computing Surveys (CSUR)* 53, 3 (2020), 1–43.

[13] Jeremy Clark, Didem Demirag, and Seyedehmahsa Moosavi. 2019. SoK: Demystifying Stablecoins. *Available at SSRN 3466371* (2019).

[14] Compound. Last Accessed: Oct. 2020. Compound. https://compound.finance/.

[15] Compound. Last Accessed: Oct. 2020. Compound. compound.finance.

[16] Philip Daian, Steven Goldfeder, Tyler Kell, Yunqi Li, Xueyuan Zhao, Iddo Bentov, Lorenz Breidenbach, and Ari Juels. 2019. Flash boys 2.0: Frontrunning, transaction reordering, and consensus instability in decentralized exchanges. *arXiv preprint arXiv:1904.05234* (2019).

[17] defiprime. Last Accessed: Sep. 2020. DeFi and Open Finance. https://www.defiprime.com.

[18] defipulse. Last Accessed: Sep. 2020. DEFI PULSE. https://www.defipulse.com/.

[19] dYdX. Last Accessed: Sep. 2020. dYdX. dydx.exchange.

[20] Shayan Eskandari, Seyedehmahsa Moosavi, and Jeremy Clark. 2019. Sok: Transparent dishonesty: front-running attacks on blockchain. In *International Conference on Financial Cryptography and Data Security*. Springer, 170–189.

[21] etherscan. Last Accessed: Oct. 2020. Hack 1 on bZx with flash loan provided by bZx. etherscan.io/tx/0xb5c8bd9430b6cc87a0e2fe110ece6bf527fa4f170a4bc8cd032f768fc5219838.

[22] etherscan. Last Accessed: Oct. 2020. Hack 2 on bZx with flash loan provided by bZx. etherscan.io/tx/0x762881b07feb63c436dee38edd4ff1f7a74c33091e534af56c9f7d49b5ecac15.

[23] etherscan. Last Accessed: Oct. 2020. Hack on Balancer with flash loan provided by dYdX. etherscan.io/tx/0x013be97768b702fe8eccef1a40544d5ecb3c1961ad5f87fee4d16fdc08c78106.

[24] etherscan. Last Accessed: Oct. 2020. Hack on EMN with flash loan provided by UniswapV2. etherscan.io/tx/0x3503253131644dd9f52802d071de74e456570374d586ddd640159cf6fb9b8ad8.

[25] Ying Fu, Meng Ren, Fuchen Ma, Heyuan Shi, Xin Yang, Yu Jiang, Huizhong Li, and Xiang Shi. 2019. EVMFuzzer: detect EVM vulnerabilities via fuzz testing. In *Proceedings of the 2019 27th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*. ACM, 1110–1114.

[26] Furucombo. Last Accessed: Sep. 2020. Furucombo. furucombo.app.

[27] Neville Grech, Michael Kong, Anton Jurisevic, Lexi Brent, Bernhard Scholz, and Yannis Smaragdakis. 2018. Madmax: Surviving out-of-gas conditions in ethereum smart contracts. *Proceedings of the ACM on Programming Languages* 2, OOPSLA (2018), 1–27.

[28] Gustavo Grieco, Will Song, Artur Cygan, Josselin Feist, and Alex Groce. 2020. Echidna: effective, usable, and fast fuzzing for smart contracts. In *Proceedings of the 29th ACM SIGSOFT International Symposium on Software Testing and Analysis*. 557–560.

[29] Lewis Gudgeon, Daniel Perez, Dominik Harz, Arthur Gervais, and Benjamin Livshits. 2020. The Decentralized Financial Crisis: Attacking DeFi. *arXiv preprint arXiv:2002.08099* (2020).

[30] Bo Jiang, Ye Liu, and WK Chan. 2018. Contractfuzzer: Fuzzing smart contracts for vulnerability detection. In *Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering*. ACM, 259–269.

[31] Sukrit Kalra, Seep Goel, Mohan Dhawan, and Subodh Sharma. 2018. Zeus: Analyzing safety of smart contracts. In *25th Annual Network and Distributed System Security Symposium, NDSS*. 18–21.

[32] Josh Kamps and Bennett Kleinberg. 2018. To the moon: defining and detecting cryptocurrency pump-and-dumps. *Crime Science* 7, 1 (2018), 18.

[33] Johannes Krupp and Christian Rossow. 2018. teether: Gnawing at ethereum to automatically exploit smart contracts. In *27th {USENIX} Security Symposium ({USENIX} Security 18)*. 1317–1333.

[34] Kyber. Last Accessed: Oct. 2020. Kyber Swap. www.kyberswap.com.

[35] Xiaoqi Li, Peng Jiang, Ting Chen, Xiapu Luo, and Qiaoyan Wen. 2017. A survey on the security of blockchain systems. *Future Generation Computer Systems* (2017).

[36] Iuon-Chang Lin and Tzu-Chun Liao. 2017. A Survey of Blockchain Security Issues and Challenges. *IJ Network Security* 19, 5 (2017), 653–659.

[37] Bowen Liu and Pawel Szalachowski. 2020. A First Look into DeFi Oracles. *arXiv preprint arXiv:2005.04377* (2020).

[38] Loi Luu, Duc-Hiep Chu, Hrishi Olickel, Prateek Saxena, and Aquinas Hobor. 2016. Making smart contracts smarter. In *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*. ACM, 254–269.

[39] Maker. Last Accessed: Sep. 2020. DAI Token. etherscan.io/token/0x6b175474e89094c44da98b954eedeac495271d0f.

[40] MakerDAO. Last Accessed: Oct. 2020. MakerDAO. makerdao.com.

[41] Amani Moin, Emin Gün Sirer, and Kevin Sekniqi. 2019. A Classification Framework for Stablecoin Designs. *arXiv preprint arXiv:1910.10098* (2019).

[42] Satoshi Nakamoto et al. 2008. Bitcoin: A peer-to-peer electronic cash system. (2008).

[43] Ingolf GA Pernice, Sebastian Henningsen, Roman Proskalovich, Martin Florian, Hermann Elendner, and Björn Scheuermann. 2019. Monetary stabilization in cryptocurrencies–design approaches and open questions. In *2019 Crypto Valley Conference on Blockchain Technology (CVCBT)*. IEEE, 47–59.

[44] Kaihua Qin, Liyi Zhou, Benjamin Livshits, and Arthur Gervais. 2020. Attacking the DeFi Ecosystem with Flash Loans for Fun and Profit. *arXiv preprint arXiv:2003.03810* (2020).

[45] DeFi Saver. Last Accessed: Oct. 2020. DeFi Saver. defisaver.com.

[46] Sergei Tikhomirov, Ekaterina Voskresenskaya, Ivan Ivanitskiy, Ramil Takhaviev, Evgeny Marchenko, and Yaroslav Alexandrov. 2018. Smartcheck: Static analysis of ethereum smart contracts. In *Proceedings of the 1st International Workshop on Emerging Trends in Software Engineering for Blockchain*. 9–16.

[47] Uniswap. Last Accessed: Sep. 2020. Uniswap. uniswap.org.

[48] Gavin Wood. 2014. Ethereum: A secure decentralised generalised transaction ledger. *Ethereum project yellow paper* 151 (2014), 1–32.

[49] Lei Wu, Siwei Wu, Yajin Zhou, Runhuai Li, Zhi Wang, Xiapu Luo, Cong Wang, and Kui Ren. 2020. EthScope: A Transaction-centric Security Analytics Framework to Detect Malicious Smart Contracts on Ethereum. *arXiv preprint arXiv:2005.08278* (2020).

[50] Valentin Wüstholz and Maria Christakis. 2019. Harvey: A greybox fuzzer for smart contracts. *arXiv preprint arXiv:1905.06944* (2019).

[51] Jiahua Xu and Benjamin Livshits. 2019. The anatomy of a cryptocurrency pump-and-dump scheme. In *28th {USENIX} Security Symposium ({USENIX} Security 19)*. 1609–1625.

[52] Yearn.finance (YFI). Last Accessed: Sep. 2020. EMN Token. etherscan.io/token/0x8b31d4A56dD29d18C817ef0fA3990d30ECC5D89b.

[53] Yearn.finance (YFI). Last Accessed: Sep. 2020. Smart Contract of Eminance Currency. etherscan.io/address/0x5ade7ae8660293f2ebfcefaba91d141d72d221e8.

[54] Micah Zoltu. 2020. How to turn $20M into $340M in 15 seconds. https://medium.com/coinmonks/how-to-turn-20m-into-340m-in-15-seconds-48d161a42311.