Anti-Sybil Project

To Build an Intelligent Sybil Discovery LEGO

Trusta Labs

Agenda



1. Introduction

- 1. Team
- 2. Deliverables (github & demo video)
- 2. Our Works
 - 1. Data Preparation
 - 2. Topic 1: Bulk Transfers & Donations
 - 3. Topic 2: Sequential Behavior Pattern Mining
 - 4. Topic 3 : Asset-Transfer Graph Mining
 - 5. Topic 4: Grant Fraud
- 3. Summary, Suggestion and Future Works

Team and Deliverables

Team

We are a team of web3 data scientists aiming at preventing sybil attacks. Before the Gitcoin Hackthon, we have already done a lot of preparations and related works, such as the Sybil analysis on HOP and Gnosis Safe airdrop. We position our work as the algorithmic detection LEGO in a Sybil resistance system although it means high development and maintenance cost.

Deliverables

The ppt contains our thinking, logic, methodology, algorithms and reasoning on a bunch of cases.

We have also uploaded the code to collect data, conduct feature engineering, compute risk score and Sybil clusters, and generate visualizations.

We keep on building an anti-sybil system. Look forward to collaborating with data scientists from Gitcoin community in Sybil hunting.

Agenda



1. Introduction

- 1. Team
- 2. Deliverables (github & demo video)
- 2. Our Works
 - 1. Data Preparation
 - 2. Topic 1: Bulk Transfers & Donations
 - 3. Topic 2: Sequential Behavior Pattern Mining
 - 4. Topic 3: Asset-Transfer Graph Mining
 - 5. Topic 4: Grant Fraud
- 3. Summary, Suggestion and Future Works

Data Preparation

Collected Data

- Gitcoin-Hackthon: GR15 donation detailed info GR_15_DATA
- Alchemy: Ethereum and Polygon transfers related to GR15 contributors
- <u>zkSync</u>: L2 transfers related to GR15 contributors
- Chainbase: token prices in USD
- DUNE: GR15 address tags from "GR15-bignode-name"

SI	tat	is:	tic	25

Table	Description	Size
grants_applications	grants info and description	808
contributions_dataset	Contributions record	475046
grants	List of grants	1503
experiment_on_chain_data	On-chain info about a small number of contributors	35
experiment_participant	Gitcoin info about some contributors	119
experiment_passport_stamp	Passport info about some contributors	574
experiment_vote	Vote record	14562
ethereum_transfer	Ethereum transfers related to GR15 contributors	8949267
polygon_transfer	Polygon transfers related to GR15 contributors	10915653
zksync_transfer	Zksync transfers related to GR15 contributors	2329056
contract_tag	Smart contract tags, e.g. opensea, binance	594949

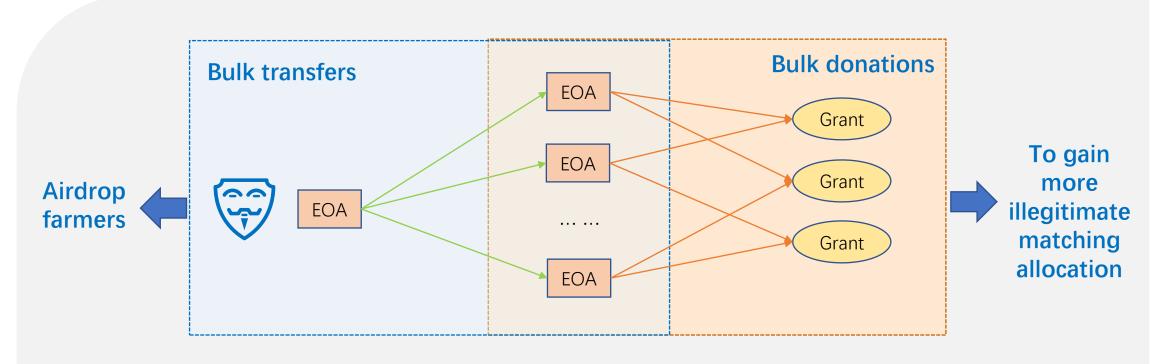
- **2022-09-07 15:00:00** ~ **2022-09-22 23:59:59**
- 1440 Grants and 55585 Contributor Addresses
- 4 Chains (Ethereum L1, zkSync L2, Polygon and Celo) 38 tokens (Eth, USDT, USDC, DAI, MATIC, WETH, etc)

Agenda



- 1. Introduction
 - 1. Team
 - 2. Deliverables (github & demo video)
- 2. Our Works
 - 1. Data Preparation
 - 2. Topic 1: Bulk Transfers & Donations
 - 3. Topic 2: Sequential Behavior Pattern Mining
 - 4. Topic 3: Asset-Transfer Graph Mining
 - 5. Topic 4: Grant Fraud
- 3. Summary, Suggestion and Future Works

Bulk Operations: Transfers & Donations

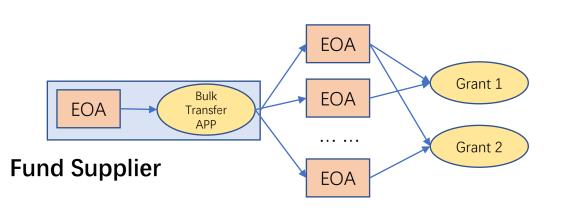


On Gitcoin platform, the sybil attack means that a user spreads their funds across multiple addresses and makes donation to the same project(s). We propose to detect Sybils by examining

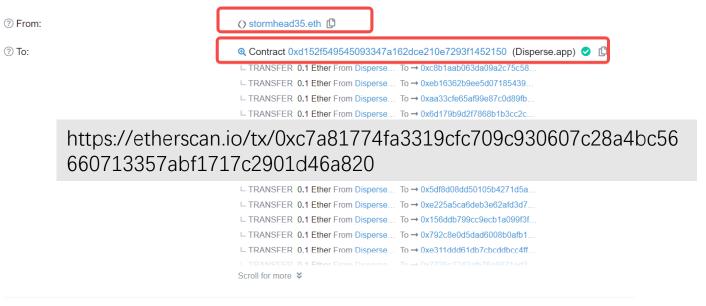
- 1. (Bulk Transfers) how the user spreads funds in a bulk way
- 2. (Bulk Donations) In what pattern they make donation to the same Grant(s)

Bulk Transfers Mining

Bulk transfer for fund preparations



An Real Example



Goal

- 1. Have a better understanding of What tools and How the sybils use for their fund preparations
- 2. Collect all the related addresses and sort them in terms of their sybils risks

Select Bulk
Transactions & Transfers



Design and Compute Risk Indicators (RIs)



Design and Compute
Sybil Scorecard from RIs

Select Bulk
Transaction & Transfers



Design and Compute Risk Indicators (RIs)



Design and Compute

Sybil Scorecard from RIs

(/ta_addr1 amount1)	Txn_hash	From	Time	Transfers_List
XXX XXX XXX (to_addr3,amount2,) (to_addr3,amount3,)}	XXX	XXX	XXX	(to_addr3,amount3,)

... ...

A bulk transaction contains more than one transfers where all transfers have an identical sender address and every transfer may have different recipient address.

So, We select Bulk Transfers in a table where

- (1) Every row corresponds to a bulk transaction
- (2) The single sender is recorded, as well as the time
- (3) A list of transfers where every transfer is represented by the to_addr, and amount

Select Bulk
Transaction & Transfers



Design and Compute Risk Indicators (RIs)



Design and Compute

Sybil Scorecard from RIs

The Six Risk Indicators

NumOfContr: The number of contributors in a transaction

ContrRatio: The number of contributors divided by the total number of distinct recipients in the transaction

ContrAmountRatio: The total amount of donations divide by the total amount of transfers-in

NumOfDistinctAmount: The number of distinct amount of transfers in a transaction

MaxAmount: The maximum amount of the transfers in the transaction

GapDay: The time difference between the transfer and donation

the greater the indicator, the greater the risk

the greater the indicator, the less the risk

Supervised Machine
Learning Algorithm

Select Bulk
Transaction & Transfers

Design and Compute
Risk Indicators (RIs)

Supervised Machine
Learning Algorithm

Design and Compute
Sybil Scorecard from RIs

Scorecard Results:

- 1. There are 21045 contributor addresses related to bulk transfers.
- 2. Based on the 6 RIs, we manually designed a scorecard, and the score distribution is

Score	0	1	2	3	4	5	6	7	8	9	10	11	12	13
NumOf Addr	9	689	1189	1841	3428	3703	3677	2436	1604	1592	537	256	71	13

- 3. We suggest that
 - Score > 9 (705 addresses), Risk = High
 - Score>7 and < 9, Risk = Medium
 - Score < 9, Risk = Low;

Example 1

Addr Txn_hash	NumOfContr	NumOfDistinctAmount	MaxAmount	ContrRatio	GapDay	ContrAmountRatio	Score
0xf4d84adf0xceab15a8	37 out of 39	1	0.05	0.948717949	0	0.339129489	11
0x2f3e38240xceab15a8	37 out of 39	1	0.05	0.948717949	0	0.110870539	11
0x8dd578e 0xceab15a8	37 out of 39	1	0.05	0.948717949	1	0.165388424	10
0xc8609af20xceab15a8	37 out of 39	1	0.05	0.948717949	1	0.152663807	10
0xc7bf129t0xceab15a8	37 out of 39	1	0.05	0.948717949	0	0.179150249	11
0x0e0e131 0xceab15a8	37 out of 39	1	0.05	0.948717949	0	0.083176408	11
0x0e0e131 0xceab15a8	37 out of 39	1	0.05	0.948717949	0	0.083176408	11
0x21f726920xceab15a8	37 out of 39	1	0.05	0.948717949	0	0.169564745	11
0x4a3fe89(0xceab15a8	37 out of 39	1	0.05	0.948717949	0	0.166366635	11
0x329b45e 0xceab15a8	37 out of 39	1	0.05	0.948717949	0	0.169564745	11
0xd9ea00a 0xceab15a8	37 out of 39	1	0.05	0.948717949	0	0.060138161	9
0x4f64a42t0xceab15a8	37 out of 39	1	0.05	0.948717949	1	0.082694212	10
0x4f64a42t0xceab15a8	37 out of 39	1	0.05	0.948717949	1	0.082694212	10

Reasoning:

- The transaction has 39 recipients, and 37 of them contributed to Gitcoin GR15. We report the 37 addresses out of 39 as a sybil cluster.
- In the same transaction, they equally received 0.05ETH from the same sender. The transaction are called by the disperse app.
- At the same day or one day later, they contributed to GR15.
- According to the 6 Ris, the Score is mostly 10 and 11 indicating very high likelihood to be sybil

ClusterID: 32

ClusterSize: 37

Discovered by: bulk transfer

RiskLevel: High

Some Noteworthy Bulk Transfer Apps (1)

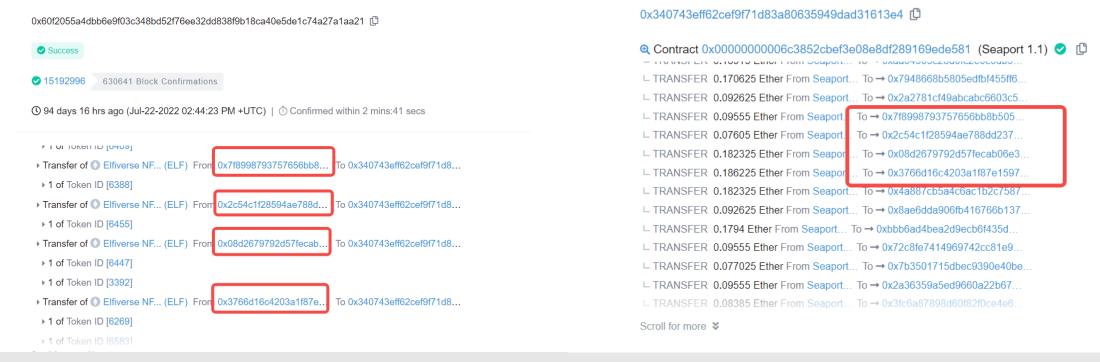
Арр	Smart Contract	Website	Description	
multisender	'0xa5025faba6e70b84f74e9b1113e5f7f4e7f4859f'	https://multisender.app/	Send ERC20 Token or ETH to thousands of addres ses out in 1 single transaction with Token Multisen der.	
disperse	'0xd152f549545093347a162dce210e7293f1452150'	https://disperse.app/	Distribute ether or tokens to multiple addresses	
bulksender	'0xd1917932a7db6af687b523d5db5d7f5c2734763f'	https://bulksender.app/	Token bulksender	
aztec_v2	'0xff1f2b4adb9df6fc8eafecdcbf96a2b351680455'	https://aztec.network/	The programmable privacy layer for web3	
across_v2	0x4d9079bb4165aeb4084c526a32695dcfd2f77381	https://across.to/	Across is a cross-chain bridge that prides itself on its speed, security and low fees.	
gnosis_safe	'0x0094477dfd27b9d5dc7ba610f26f0dd4ae64db5b', '0x 81b2e8b475295f4254a38433b6739efe270fc88b', '0xb32 aebf09cb331f853536b4370be8acf2d886775', '0xa788e3 0d0cd4d15f2159c686ff2ce8cf4be2c125', '0xa653ecfdd7 987dd9b6bc284c3abd22bdb199159c'	https://gnosis.io/safe/	Smart contract-based multisig wallet	

It is not necessary for an address to be a sybil if it uses these applications, but it is an importance signal.

Some Noteworthy Bulk Transfer Apps (2)

NFT marketplace Apps

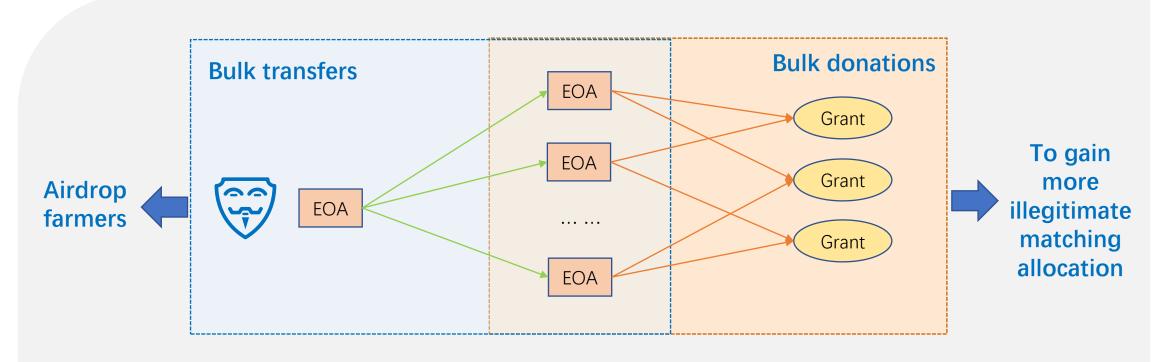
- opensea&seaport, element_ex, ragnarok (Looksrare), async.art, rarible. boredapeyogaclub_v2
- Bulk NFT trades cause bulk fund transfers to contributors.



https://etherscan.io/tx/0x60f2055a4dbb6e9f03c348bd52f76ee32dd838f9b18ca40e5de1c74a27a1aa21

The contributors sold the same NFTs in one transaction. And then received funds from the same buyer simultaneously.

Bulk Operations: Transfers & Donations



On Gitcoin platform, the sybil attack means that a user spreads their funds across multiple addresses and makes donation to the same project(s). We propose to detect Sybils by examining

- 1. (Bulk Transfers) how the user spreads funds in a bulk way
- 2. (Bulk Donations) In what pattern they make donation to the same Grant(s)

Bulk Donations Mining: Data and Idea

Table containing detailed contribution Information

Grant	txn_id	txn_hash	Time	Token	Amount						
Address 1											
Address 2	Table h	Table has the detailed contribution info with									
Address 3	respect	respect to a grant, such as the contributor									
	addres	address, txn ID and txn hash, the time of donation									
Address m	and the	e token and	amoun	t of the d	onation et	C.					

The Idea

Attackers (or farmers) invest their time (to manipulate) and money (to donate) to perform Sybil attacks.

Definitely they prefer to have a higher ROI (Return on investment).

Here are some assumptions as to greedy Sybils:

- 1. They donate the same grant
- 2. They donate as small amount as possible
- 3. They make use of script/tools to donate with the same parameter setting such as ChainID, Layer of Chain, token, amount
- 4. They donate in a sequential way, very closely

Indicators(Or Variables) and Scores

We encode our plain English assumptions as filtering variables

Var3: Group1Proportion

NumOfAddresses in Group1 divided by the total number of addresses in the grant

Var2: #ContributionsGroup1 NumOfContributions in Group1

Grouping Criteria 1:

- Same Grant
- Same Chain
- Same Network
- Same Token
- Same Amount

Var6: Q3TimeDifferences

The 3rd quartile (Q3) of the time differences between successive donations

Var5: Group2Proportion

NumOfAddresses in Group2 divided by the total number of addresses in the grant

Var7: CVTimeDifferences

The coefficient of variation of the time differences between successive donations

Var4: #ContributionsGroup2

NumOfContributions in Group2

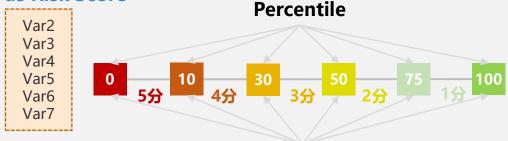
Var1: Amount

Grouping Criteria 2:

Same grouping criteria as of grouping 1

Time differences between two successive donations are <=30mins

Var as Risk Score



Score

Var1 (Amount):

< 1U: 5分; >1U and <=1.1U: 4分; =1U: 3分; >1.1U and <=1.3U: 2分; >1.3U: 1分

Scoring donation and address

Donation Risk Score: $S_{donation} = \sum_{i=1}^{7} S_i$

Address Risk Score:

 $S_{address} = MAX (S_{donation 1}, \dots, S_{donation n})$

Where **donation 1** to **donation n** are donated by current address.

Results and Risk Level

Score Distribution

Trans Score	Trans CNT	Address CNT	Trans PCT	Address PCT
30	351	132	0.1%	0.2%
29	240	94	0.1%	0.2%
28	1,343	520	0.3%	0.9%
27	2,461	818	0.6%	1.5%
26	3,002	869	0.8%	1.6%
25	4,722	1,484	1.2%	2.7%
24	5,904	1,769	1.5%	3.2%
23	6,665	1,880	1.7%	3.4%
22	7,367	1,825	1.8%	3.3%
21	7,523	1,656	1.9%	3.0%
20	8,479	1,867	2.1%	3.4%
19	9,383	2,190	2.4%	4.0%
18	8,003	1,783	2.0%	3.2%
17	7,359	1,587	1.8%	2.9%
16	7,016	1,589	1.8%	2.9%
15	6,925	1,352	1.7%	2.4%
14	5,778	1,114	1.4%	2.0%
13	4,567	739	1.1%	1.3%
12	3,177	536	0.8%	1.0%
11	1,872	386	0.5%	0.7%
10	1,159	225	0.3%	0.4%
9	463	89	0.1%	0.2%
8	46	18	0.0%	0.0%
7	36	3	0.0%	0.0%
0	295,373	30,778	74.0%	55.7%

Risk Levels

• **High: Score** >= 21

#OfAddress: **14005**, **25.3**%

Medium: Score < 21 and Score > 0

#OfAddress: **16040**, **29.0**%

• Low: Score = 0

#OfAddress: 25258, 45.7%

** Note: the total number reported also includes results of another thread on bulk donations

Example 1: Sybils Manipulated by the Same UserID

The 10 Sybil Donations

address	address					mount
	0x7edb5ed01fd0c42ea3273fc1cb1f8943b12978ad					1.4
0xa94110480a20d10afb04a7aa58aa00068002fa	23	2022-09-21 11:27:04	0.37	th_zksync	DAI	1.4
0xca5d94ab99 Grant ID: 7202		2022-09-21 11:27:26	0.40	th_zksync	DAI	1.4
0x46dbaecb16 Cluster ID: 77809		2022-09-21 11:27:50	0.37	th_zksync	DAI	1.4
0x350d84d0ed Cluster Size: 10		2022-09-21 11:28:12	0.37	th_zksync	DAI	1.4
0xcd2519d2f3		2022-09-21 11:28:34	0.40	th_zksync	DAI	1.4
0xfe565cd155 Discovered by: bulkdonation		2022-09-21 11:28:58	0.38	th_zksync	DAI	1.4
0x6f3d616590 RiskLevel: High		2022-09-21 11:29:21	0.42	th_zksync	DAI	1.4
0x101bec121c54810bdacd32c99304819810bc5bd	ia	2022-09-21 11:29:46	0.62	th_zksync	DAI	1.4
0xd704bf5cc05ff8465903da4c515eb223b5f2eb4	lf_	2022-09-21 11:30:23	•	th_zksync	DAI	1.4

Some Normal Donations

				Ц	
time	time_gap	chain	tokei		amount
2022-09-08 05:52:59	41.87	th_std	DAI		1. 16
2022-09-08 06:34:51	38. 43	th_zksync	DAI		25.00
2022-09-08 07:13:17	100. 77	th_zksync	USDC	П	1. 22
2022-09-08 08:54:03	57. 52	th_std	ETH	П	1. 15
2022-09-08 09:51:34	47. 07	th_std	DAI	П	1.05
2022-09-08 10:38:38	94. 30	th_zksync	ETH	П	1.31
2022-09-08 12:12:56	115. 27	th_polygor	USDC	П	1. 10
2022-09-08 14:08:12	40. 33	th_zksync	ETH	П	1. 14
2022-09-08 14:48:32	20. 70	th_polygor	MATIC	П	1. 25
2022-09-08 15:09:14	29. 63	th_zksync	DAI		1.02
2022-09-08 15:38:52		th_std	ETH		32.64

Reasoning

The same Gitcoin User (UserID= e18388e14838506df27f901c8b62de6c4fd6c Da5b5e332e955b078fe6482bc96) made 10 donations to GrantID=7202 with 10 wallets. These happened in 4 mins, with a very close time interval = 30 secs between every two successive donations. Every wallet contributed 1.4U DAI on zkSync.

On the contrary, normal donations do not have apparent pattern in token aggregation, amount aggregation and chain aggregations. The time intervals between every successive donations are not all small.

Example 2: Donations with Same & Small Amounts

Reasoning

Within about 2 hours, there are 61 donations to Grant 6713. The time intervals are as small as 30 secs to 1 minute. Every addresses donate 0.086U MATIC on polygon.

			t i m a	time man	ahaia	4 alsos	-mount
	address		time	time_gap	chain	toker	amount
0x119b9	dbe4a5e3fae94fce23511562a0dd78	3cb6d3	2022-09-15 12:18:32	2. 25 e	t_polygon	MATIC	0.086
0xf91cd9	9bfc08d1df946138fa582428491d2a	a78778	2022-09-15 12:20:47	1.50 e	t polygon	MATIC	0.086
0x930df0	074acf694238bdf6e1c947e1c5442d	d5f019	2022-09-15 12:22:17	1. 27 e	th_polygon	MATIC	0.086
0x2da18	leda79285e810ebcab3eec32c706aa	a28a9c	2022-09-15 12:23:33	1. 23 e	eth_polygon	MATIC	0.086
0x5df8d0	08dd50105b4271d5ad07d094ace85	cf0ee6	2022-09-15 12:24:47	2.00 e	et _polygon	MATIC	0.086
0x6d179l	o9d2f7868b1b3cc2cd5b3e93eb0eb9	9d1174	2022-09-15 12:26:47	0. 98 e	th_polygon	MATIC	0.086
0x792c8e	e0d5dad6008b0afb1c5a4565b160a9	965485	2022-09-15 12:27:46	3. 35 e	et _polygon	MATIC	0.086
0xe311de	dd61db7cbcddbcc4ffb8ac68eff6b7	7820df	2022-09-15 12:31:07	2.45 e	t _polygon	MATIC	0.086
0x7725c3	3242afb76e9871ad3e7c879f4c6d5	db0092	2022-09-15 12:33:34	1.30 e	t _polygon	MATIC	0.086
0x5ff1de	1c7da0200720060b1227affd761ad	665b7e	2022-09-15 12:34:52	1. 13 e	t _polygon	MATIC	0.086
0x5ba36'	Grant ID: 6701	e03d3	2022-09-15 12:36:00	1. 17 e	t _polygon	MATIC	0.086
	Cluster ID: 250829						
	Cluster Size: 61						
	Discovered by: bulkdonation RiskLevel: High						
0x1e6c3	C 2004eco021D000110De0001eu01 D	336501	2022-09-15 14:33:08	0. 25 e	et_polygon	MATIC	0.086
0x76025	c1ebb7c6d61190761d2985c77cb2f4	464aae	2022-09-15 14:33:23	0. 27 e	etn_polygon	MATIC	0.086
0xb25169	94f56777115ca3bc840e36f9cb158	1f0883	2022-09-15 14:33:39	0. 27 e	etn_polygon	MATIC	0.086
0x844203	3780009ed82a1d2c9c220f71f8809	1f018e	2022-09-15 14:33:55	0.35 €	et _polygon	MATIC	0.086
0xa91741	o240ea4001c7b228916ce34791b11	le6fbb	2022-09-15 14:34:16		etn_polygon		0.086
0x43a23	4c2c9f698d7dc56cfb32b7dfac31f	7fe0de	2022-09-15 14:37:46	ϵ	et _polygon	MATIC	0.086

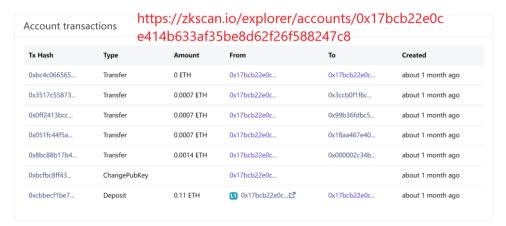
Agenda



- 1. Introduction
 - 1. Team
 - 2. Deliverables (github & demo video)
- 2. Our Works
 - 1. Data Preparation
 - 2. Topic 1: Bulk Transfers & Donations
 - 3. Topic 2: Sequential Behavior Pattern Mining
 - 4. Topic 3: Asset-Transfer Graph Mining
 - 5. Topic 4: Grant Fraud
- 3. Summary, Suggestion and Future Works

Sequential Behavior Pattern Mining

Transfer Interact Mint Claim Donate ... Asset with SC NFT Airdrop Gitcoin In the form of transactions, event, log, internal call





Make EOA(address) behavior computable so as to facilitate sybil discovery

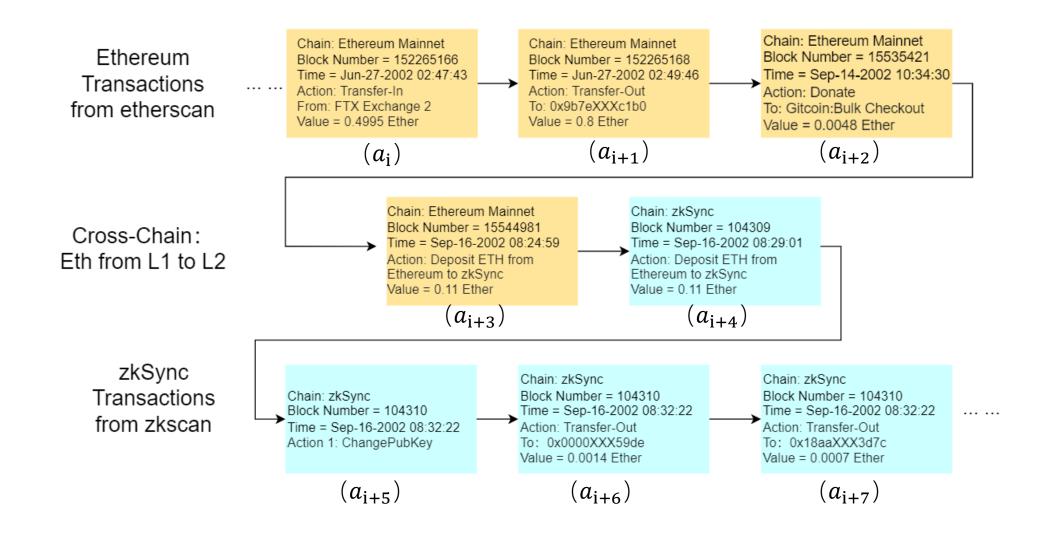
Sequential Behavior Representation

Sequential Behavior
Similarity Computation

Usecase 1
Searching

Usecase 2 Clustering

Sequential (Cross-Chain) Behavior Representation



Similarity Definition

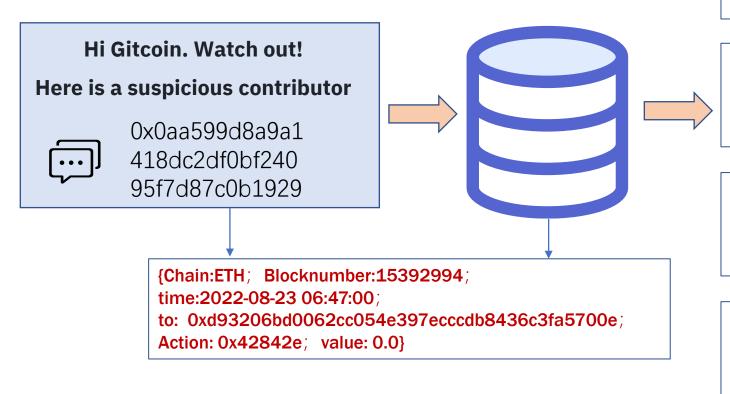
Mathematically, for EOA1's behavior $s_1=(a_1,a_2,...a_n)$ and EOA2's behavior $s_2=(b_1,b_2,...b_m)$, define that

$$sim(s_1,s_2) \ = \ 1$$
 if and only if

- (1) n=m and
- (3) for every pair of actions a_i, b_i , they are identical with only negligible time difference.

More sophisticated metrics can be experimented with in the future.

Use Case 1: Searching



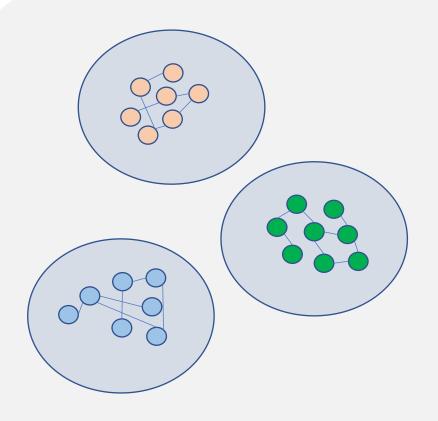
```
{ Chain:ETH; Blocknumber:15392994; time: 2022-08-23 06:47:00; to: 0xd93206bd0062cc054e397ecccdb8436c3fa5700e; Action: 0x42842e; value: 0.0}
```

{ Chain:ETH; Blocknumber:15392994; time: 2022-08-23 06:47:00; to: 0xd93206bd0062cc054e397ecccdb8436c3fa5700e; Action: 0x42842e; value: 0.0} { Chain:ETH: Blocknumber:15392994: time: 2022-08-23 06:47:00; to: 0xd93206bd0062cc054e397ecccdb8436c3fa5700e; Action:0x42842e; value: 0.0} {Chain:ETH; Blocknumber:15392994; time: 2022-08-23 06:47:00; to: 0xd93206bd0062cc054e397ecccdb8436c3fa5700e; Action: 0x42842e; value: 0.0} {Chain:ETH; Blocknumber:15392994;

time: 2022-08-23 06:47:00; to: 0xd93206bd0062cc054e397ecccdb8436c3fa5700e Action: 0x42842e; value: 0.0}

INPUT an address, OUTPUT the list of addresses having almost the same on-chain behaviors

Use Case 2: Clustering



- 1. Sequential Behavior Representation
- 2. Similarity Definition
- 3. Clustering: A variety of distance-based algorithms such as spectral clustering, hierarchical clustering can be used. Here, Connected Component Based Clustering,
 - 1. If (A,B) in a cluster; (B,C) in a cluster, then
 - 2. (A,B,C) are all in the same cluster

 Result in 115 clusters with size >=5

Cluster Size	[2,5)	[5,10)	[10,20)	[20,30)	[30,40)	[40,50)	[50,60)	=75	=192	>=5 Total
# of CLusters	380	74	19	8	6	3	3	1	1	115 Clusters (1669 Sybils)

Example 1



Reasoning

All these addresses has only 4 actions. Apparently from etherscan, the four actions are

127 days ago
Transfer in from Binance

127 days ago Deposit ETH to Arbitrum

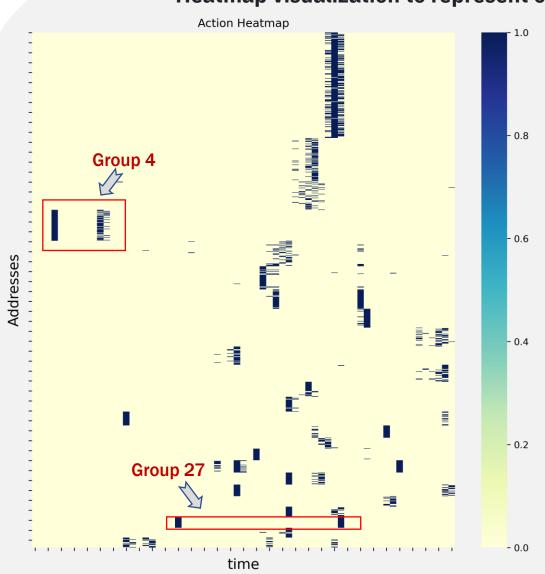
127 days ago Send to L2 via HOP Ethereum Bridge

41 days ago

Donate to Gitcoin: Bulk Checkout

Visualization and Examinations

Heatmap visualization to represent clusters behaving in a similar way



Group 4: 56 contributors

- 1. 20220907, received 0.06Eth from 56 addresses
- 2. 20220909 11am-15pm, Deposit L2 with 0.055Eth
- 3. On zkSync, they all
 - 1. Mint NFT
 - 2. Swap some ETH for DAI
 - 3. Donate GR15

Group 27: 19 contributors

- 1. 20220912, received 0.06Eth for the 1st time
- 2. 20220912 Deposit L2 with 0.055Eth
- 3. On zkSync, they all
 - 1. Mint NFT
 - 2. Swap the same amount ETH for DAI
 - 3. Donate GR15
- 4. 20220924 On L1, Interact with Socket:Registry

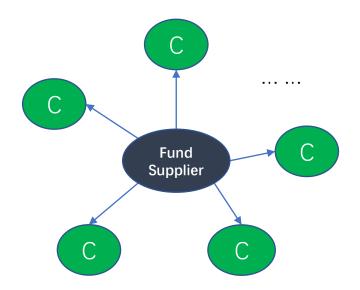
Agenda



- 1. Introduction
 - 1. Team
 - 2. Deliverables (github & demo video)
- 2. Our Works
 - 1. Data Preparation
 - 2. Topic 1: Bulk Transfers & Donations
 - 3. Topic 2: Sequential Behavior Pattern Mining
 - 4. Topic 3: Asset-Transfer Graph Mining
 - 5. Topic 4: Grant Fraud
- 3. Summary, Suggestion and Future Works

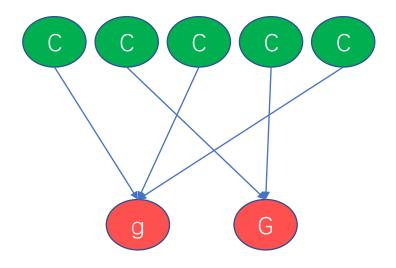
Asset-Transfer Graph (ATG)

Asset-Transfer Graph (ATG) represents the relationship between Contributors, Grants(Gitcoin), Fund Suppliers and Residual Collectors in terms of their asset (ETH, MATIC and ERC20 tokens) transfers.



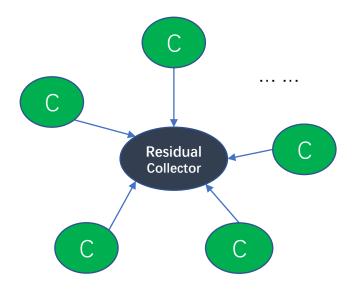
Phase1: Fund Preparation

Fund Supplier transfers funds to 1 or more contributors



Phase 2: Donation

Contributors transfer fund to grant Gitcoin to make donations



Phase 3: Residual Collection

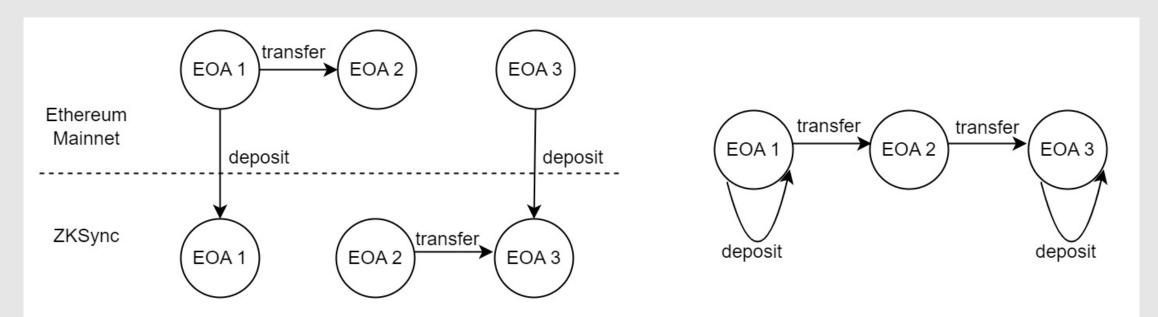
After donation, contributors transfers residual fund to residual collector

Overall Graph Constructions

Asset-Transfer: Transfers from A \rightarrow B where A OR B is a contributor

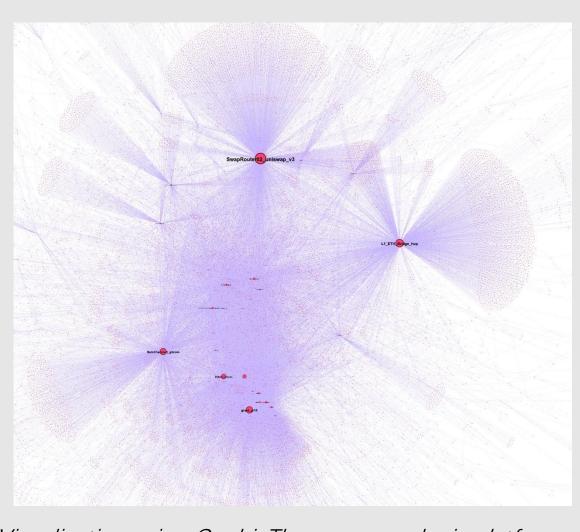
1. Include the Assets = ETH, USDC, USDT, DAI on Ethereum, Polygon and zkSync

2. Date: Sept 1st - Oct 19th ATGraph Size: 1.4M edges



The two graphs represent the same asset transfers.
As shown, Ethereum mainnet and ZKSync transfers are aggregated and illustrated in one graph.

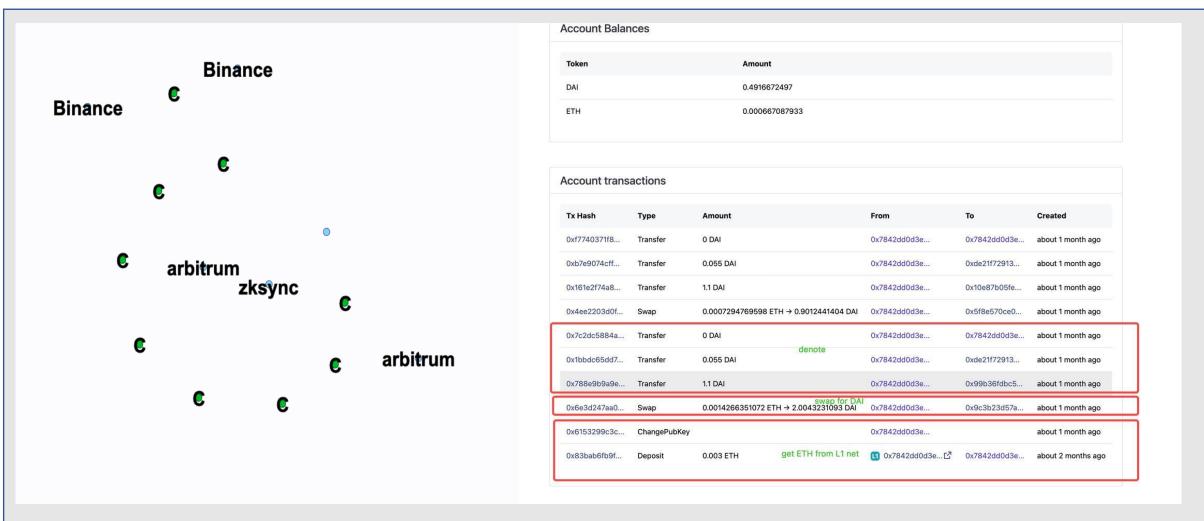
Overall Graph Visualization



Visualization using Gephi: The open graph viz platform

HUB	Label	Degree
0x7d655c57f71464b6f83811c55d84009cd9f5221c	BulkCheckout_gitcoin	52201
0x00000000006c3852cbef3e08e8df289169ede581	Seaport_seaport	33926
0xc098b2a3aa256d2140208c3de6543aaef5cd3a94	FTX Exchange 2_	30229
0xabea9132b05a70803a4e85094fd0e1800777fbef	ZkSync	17618
0x283af0b28c62c092c9727f1ee09c02ca627eb7f5	ETHRegistrarController_3na meservice	17150
0x68b3465833fb72a70ecdf485e0e4c7bd8665fc45	SwapRouter02_uniswap_v3	17035
0xc02aaa39b223fe8d0a0e5c4f27ead9083c756cc2	WETH9_zeroex	9765
0x4d9079bb4165aeb4084c526a32695dcfd2f77381	Ethereum_SpokePool_acros s_v2	9326
0x5bf5bcc5362f88721167c1068b58c60cad075aac	ProofOfStake_Pages_vitaliks _book	8919
0xff1f2b4adb9df6fc8eafecdcbf96a2b351680455	RollupProcessor_aztec_v2	8301
0x4dbd4fc535ac27206064b68ffcf827b0a60bab3f	Inbox_arbitrum	8198
0xb8901acb165ed027e32754e0ffe830802919727f	L1_ETH_Bridge_hop	6181
0x20f780a973856b93f63670377900c1d2a50a77c4	ERC721OrdersFeature_elem ent_ex	5288
0xdef1c0ded9bec7f1a1670819833240f027b25eff	ExchangeProxy_zeroex	4684

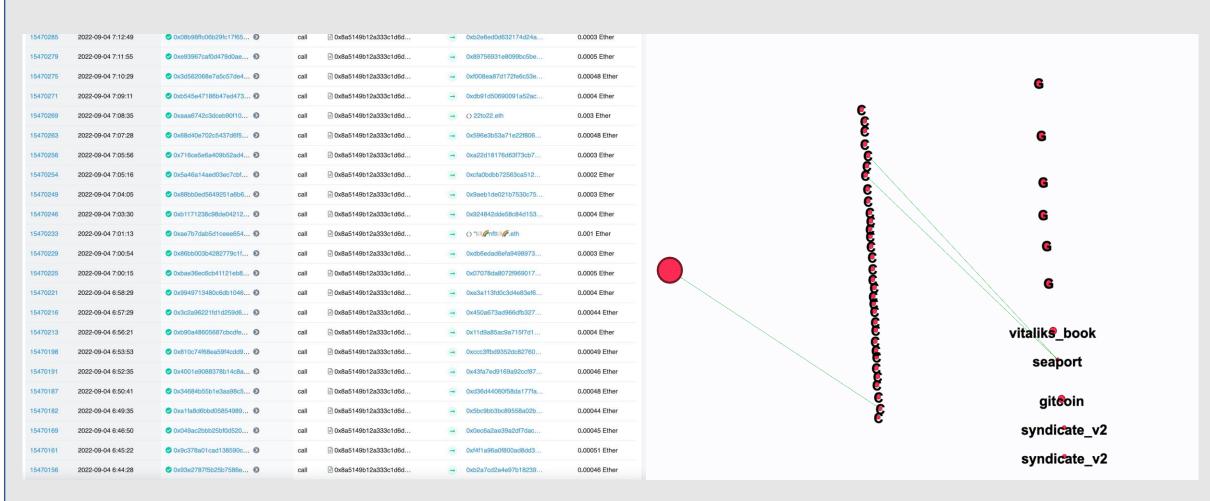
Example 1: Chain-Like Attack



- 1. ETH from Binance to the first contributor
 - 2. ETH goes through the 9 Contributors in turn

- 1. Deposit to L2, and then Swap to DAI
 - 2. Donate

Example 2: Diamond Attack

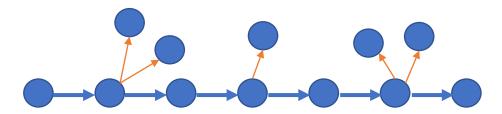


Diamond Attack:

- 1. Sep 3rd 1 address distributed ETH to 32 contributors
- 2. Donate *ProofOfStake* by Vitalik, GR15(6 grants)

Pipeline

- 1. Staring from the overall graph
- 2. Remove HUB addresses and smart contracts
- 3. Compute Weakly-Connect Components
- 4. For every WCC
- 5. Examine whether it contains Chain-Like attacks OR Diamond attacks



The heuristic to examine Chain is to prune branches so that the trunk is left as a Chain.

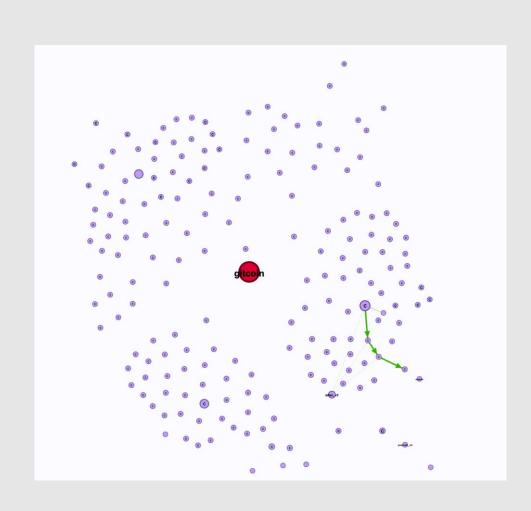
The key to find Diamond is to find the Fund Supplier with great out-degree and out-flow

- 6. Visualize possible Chain-Like attacks and Diamond attacks using Gephi
- 7. Manually double check them

Finally we have 150 Connect Components

Through carefully investigation, 2170 Addresses in the CCs are judged as Sybils (Risk = HIGH)

Example 3: Cluster With 188 Sybils



ClusterID=0 with 188 Addresses; Attack on Ethereum;

Fund Preparation:

Two addresses 0xede41(2022-09-14 9:25:49) and 0xb8308(2022-09-14 10:35:30) distributed fund in a Chain-like way.

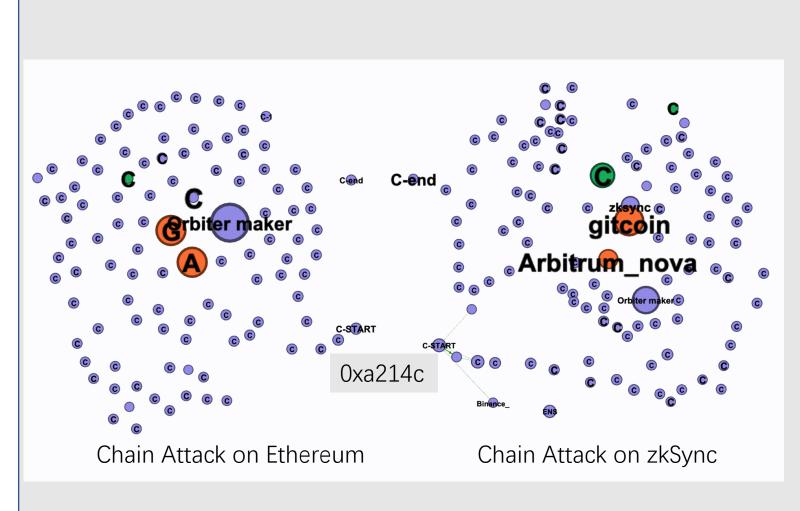
Making Donations:

With fund received, every address first made a donation of about 1USD, and then sent fund to the next.

Residual Collection:

After conducting attacks on Aztec and zkSync, all the residual funds are collected on sep 26th to three addresses on zkSync 0x45997, 0xede41 and 0xb8308.

Example 4: Cluster With 98 Sybils



ClusterID=1; 98 Addresses;
On Ethereum and zkSync simultaneous

Fund Preparation:

Address C-START distributed funds in a Chain-like way, respectively on L1 Ethereum (09-15 16:16:23) and L2 zkSync (09-15 16:17:30)

Making Donations:

With fund received, addresses first made a donation to 2 grants, and then send funds to the next.

Residual Collection:

The last address along the chain transferred all residual funds back to C-START on Ethereum.

Agenda



1. Introduction

- 1. Team
- 2. Deliverables (github & demo video)
- 2. Our Works
 - 1. Data Preparation
 - 2. Topic 1: Bulk Transfers & Donations
 - 3. Topic 2: Sequential Behavior Pattern Mining
 - 4. Topic 3: Asset-Transfer Graph Mining
 - 5. Grant Fraud
- 3. Summary, Suggestion and Future Works

Grant Fraud

Basic Info

• Grant ID: 7419

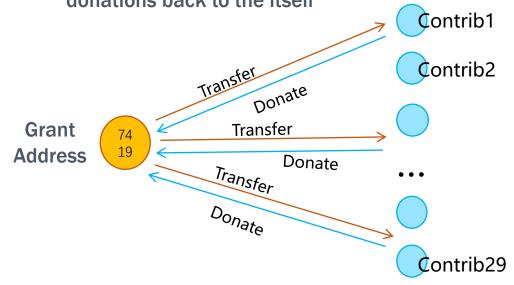
Contributors: 29

Grant Address:

0xfd9f8a0f4bdeac72f08af1c708023cc31dd2e3be

Reasoning

(1)The grant address transferred fund to 29 EOAs, and then (2) manipulated the EOAs to make donations back to the itself



Attack Details

Supply funds to EOAs (29 transfers)



Bulk donations (39 donations)

address	time	chain	token	amount
0xfc66a1f969bb77eb89a314725d657312d58f1589	2022-09-10 23:29:03	eth_std	ETH	17. 31
0x0b6426070a98451308ee54cd3b3c114f5d1a2d65	2022-09-11 17:28:42	eth_std	ETH	7. 07
0x288819c32f2228203aa9065dfa53497cc2527e69	2022-09-12 03:12:57	eth_std	ETH	1. 94
0xb869898cd011593d3d52037b743131924375e0ae	2022-09-12 20:20:00	eth_std	ETH	2.07
0x05ed44153d4cb72748595ef915118772cf189553	2022-09-13 14:04:37	eth_std	ETH	104. 45
0x83ac2bb284930f4a9acfffb7cfb0dc0c92b5ab97	2022-09-14 11:31:10	eth_std	ETH	6. 47

.

0xae86d0ad922a0abe16878913a71cdcd018a50b96	2022-09-19 14:47:38	eth_std	ETH	1. 98
0x1b5dff786eaccf5a41bf922e64313a0f4a60dab9	2022-09-19 14:47:42	eth_std	ETH	1. 98
0xcf1dc2cb1a5b5344330b01a188d0cdc62773fe5e	2022-09-19 14:51:38	eth_std	ETH	1. 98

Agenda



- 1. Introduction
 - 1. Team
 - 2. Deliverables (github & demo video)
- 2. Our Works
 - 1. Data Preparation
 - 2. Topic 1: Bulk Transfers & Donations
 - 3. Topic 2: Sequential Behavior Pattern Mining
 - 4. Topic 3: Asset-Transfer Graph Mining
 - 5. Grant Fraud
- 3. Summary, Suggestion and Future Works

Summary and Future Works

Risk Level and Address CNT

Risk Level	Final Result	Bulk Donation Risk	ATG Risk	Behavior Risk	Bulk Transfer Risk
high	16,994	14,005	2,170	1,669	705
medium	15,728	16,040	275	-	2,671
low	22,581	25,258	52,858	53,634	51,927
Total	55,303	55,303	55,303	55,303	55,303

Summary

We propose and develop four approaches, namely bulk transfers pattern mining, bulk donations pattern mining, asset-transfer graph mining, sequential behavior pattern mining for slaying sybil. These approaches form a systematic algorithmic LEGO and totally find 16,994 High Risk Sybils. Besides, we make our first attempt to detect grant fraud and find one case.

Future works

Due to time limit, some of the algorithms used in this work is not state-of-art. We can have more deep studies. It would be very grateful if we can access Gitcoin exclusive data, e.g. ip, wifi, user behavior on Gitcoin etc.

