

# DRAINLoG:

## Detecting Rogue Accounts with Illegally-obtained NFTs using Classifiers Learned on Graphs

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Network and System Security (NSS) Lab, KAIST<sup>1</sup>

Indiana University Bloomington<sup>2</sup>

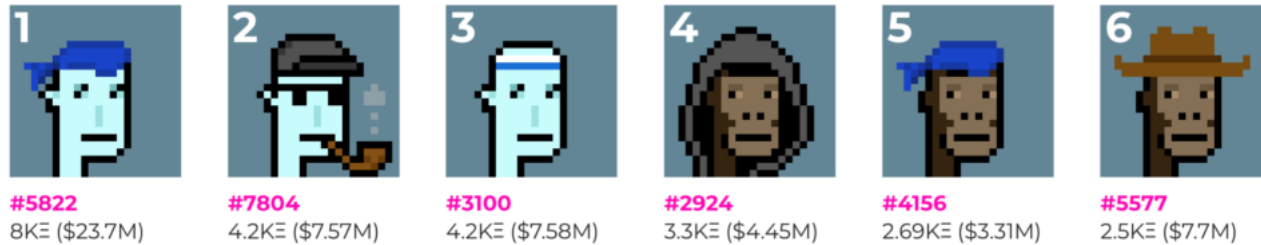
S2W Inc.<sup>3</sup>

# What is NFT?

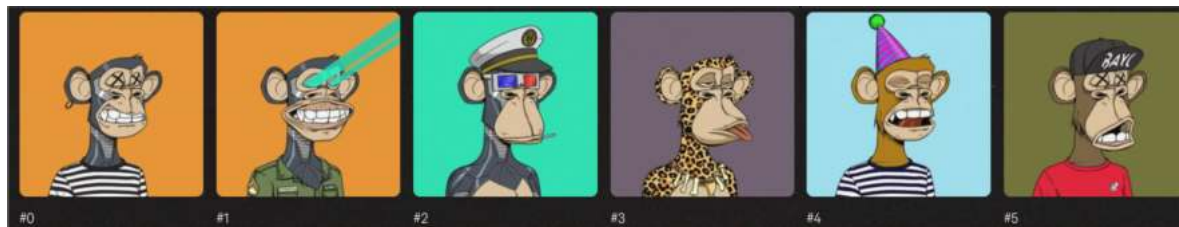
# What is NFT?

- A unique digital identifier that is recorded on a blockchain
- Widely used in various sectors, including art, gaming, and retail
- A *collection* refers to a group of NFTs sharing similar features

CryptoPunks



BA  YC

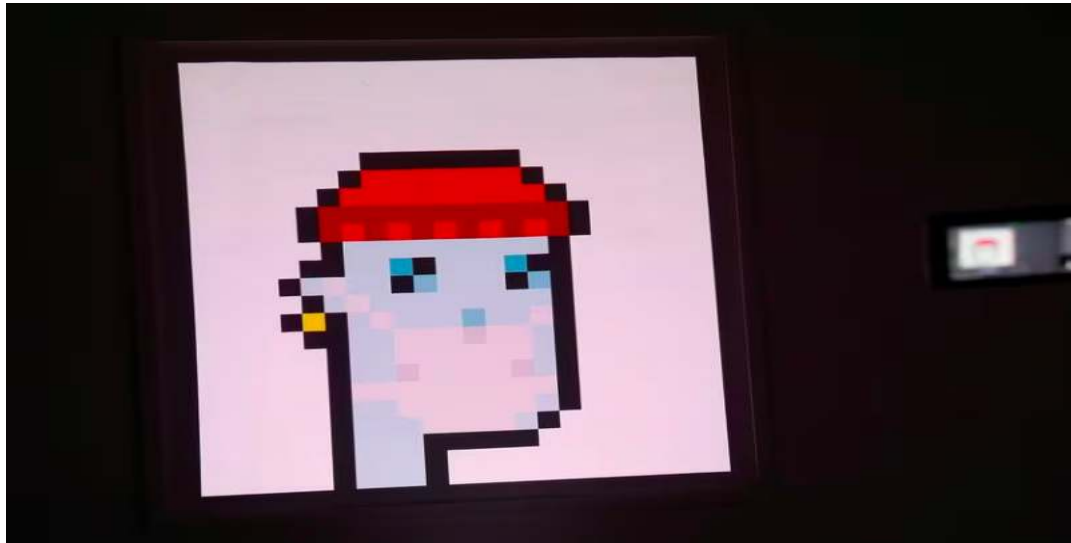


# What is NFT?

## NFT sales volume surges to \$2.5 bln in 2021 first half

By Elizabeth Howcroft

July 6, 2021 3:00 PM GMT+9 · Updated a year ago



## NFT Market Booms in January 2024 with Record Volumes



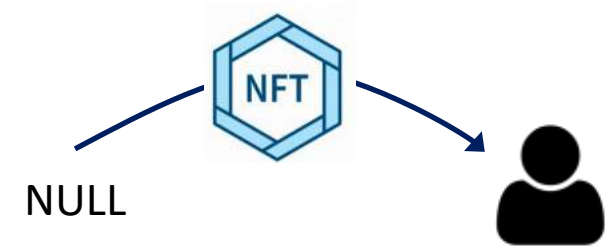
BY UMAIR YOUNAS — February 6, 2024 - 3:03 pm in nft news



# NFT transaction type

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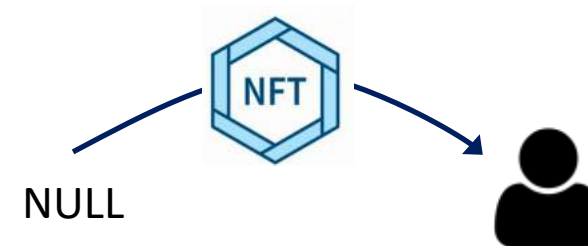
- Mint
  - Converting digital data into NFTs recorded on the blockchain
  - An NFT is created by minting



# NFT transaction type

- Mint

- Converting digital data into NFTs recorded on the blockchain
- An NFT is created by minting



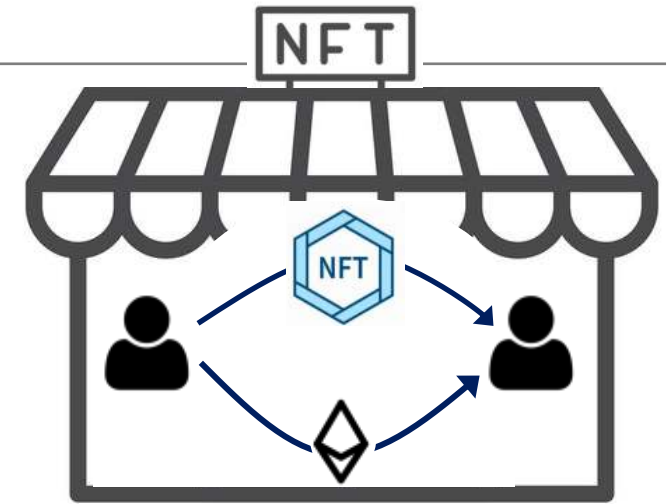
- Burn

- Sending NFTs to an inaccessible address
- Remove NFTs from circulation
- Used for various purposes, such as operating a collection's community, etc.



# NFT transaction type

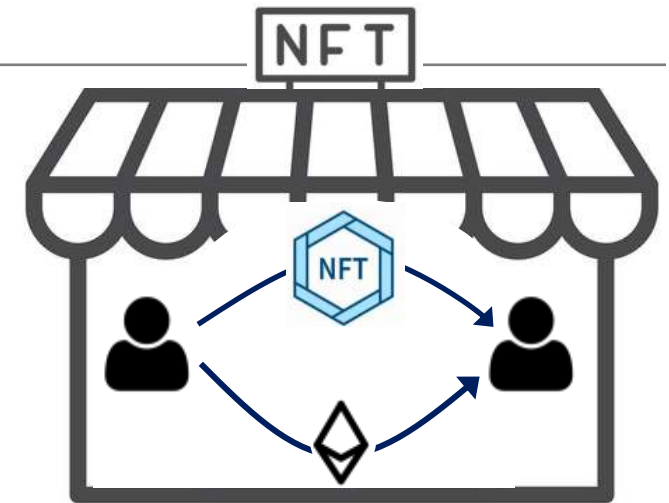
- Sale
  - Transferring an NFT ownership to another user for payment
  - NFTs are typically traded with Ether or sometimes fungible tokens through marketplaces
  - Users can partake in sales in two ways: buying and selling



# NFT transaction type

- Sale

- Transferring an NFT ownership to another user for payment
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- Gift

- Transferring an NFT ownership to another user without payment
- Typically, gifting occurs between related users such as avoid monitoring when manipulating markets
- Users can partake in gifts in two ways: gifting-in and gifting-out





# NFT phishing scams are on the rise



## Users Lose Over \$1.2M To NFT Airdrop Phishing Scam on Polygon

By [Newton Gitonga](#) - June 27, 2023



## OpenSea users targeted in phishing scam disguised as official NFT offers

By [Sarah Jansen](#) November 14, 2023 at 4:43 pm Edited by [Brian Stone](#)



## Phishing scam: NFTs Worth \$1.7M Stolen from OpenSea Users

BY [DEEBA AHMED](#) - FEBRUARY 21, 2022 - 2 MINUTE READ

## N Korean Hackers pull off NFT Phishing Scam worth 300 ETH

BY [VISMAYA V](#) PUBLISHED ON - DECEMBER 27, 2022 13:27 UPDATED ON - DECEMBER 27, 2022 13:27 2 MINUTE READ



## Bored Ape Yacht Club Hacked, Loses \$380,000 Worth of NFTs in Phishing Attack

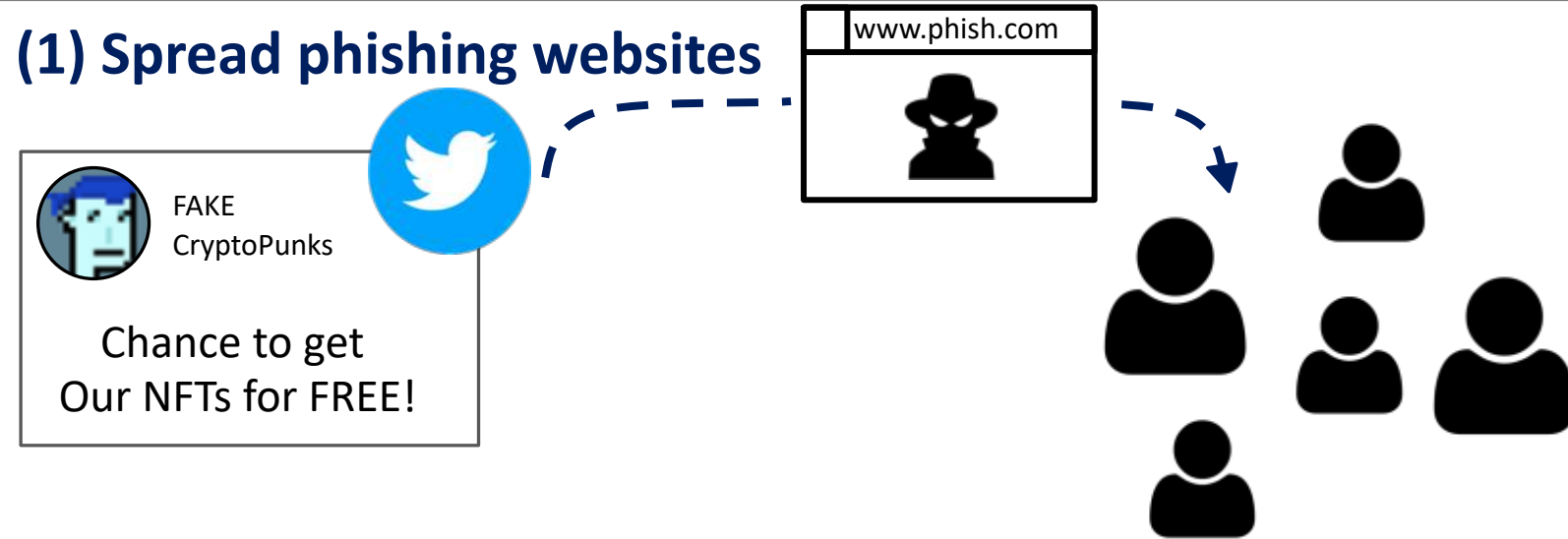
[Yaël Bizouati-Kennedy](#)

June 6, 2022 · 3 min read



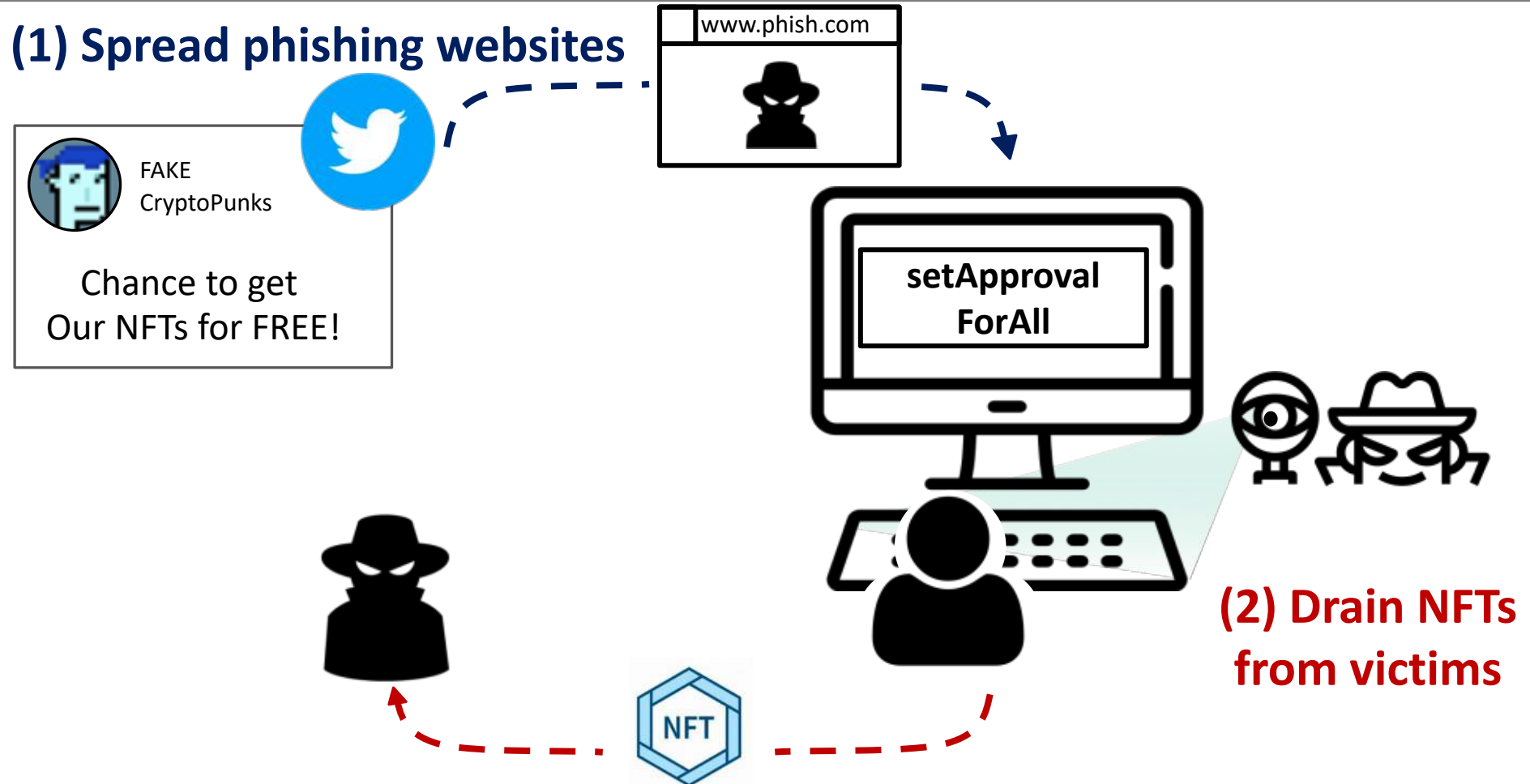
# Stealing NFTs using phishing attacks

## NFT Draining



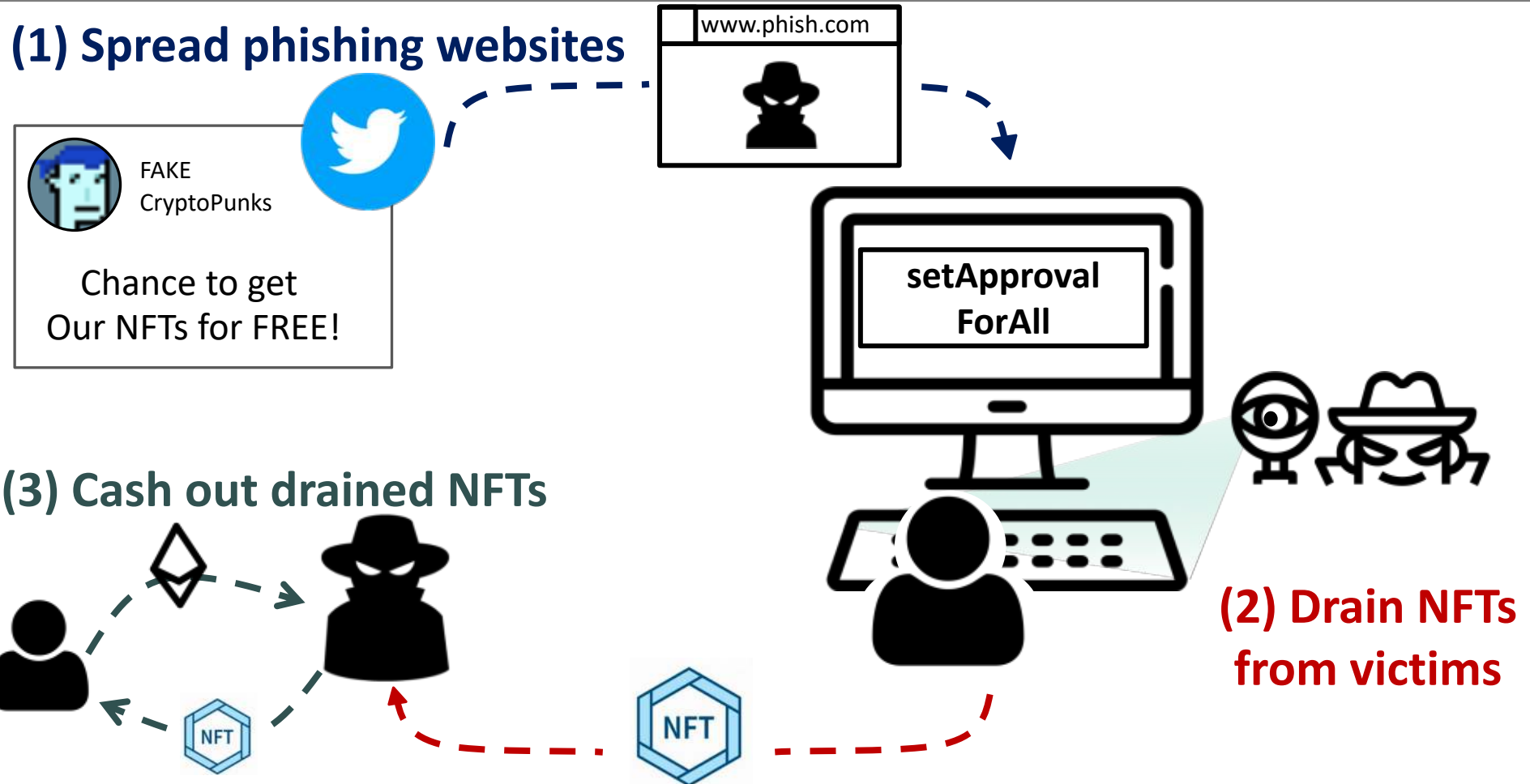
# Stealing NFTs using phishing attacks

## NFT Draining



# Stealing NFTs using phishing attacks

## NFT Draining



# Existing Countermeasures

 **OpenSea**<sup>[1]</sup>


**This item can't be bought or sold due to suspicious activity.**



**Fish Friend** 



Owned by you  7 views



 Price History


 **METAMASK**<sup>[2]</sup>

**Give permission to access all of your BoredApeYachtClub?**

By granting permission, you are allowing the following account to access your funds

 0x [redacted] 

 Site suggested > 

**Gas (estimated)**  **\$3.08 0.00186714 ETH**

[1] <https://opensea.io> [2] <https://metamask.io/>

# Existing Countermeasures



**Only effective when victims are able to notice and report it**



**Already bypassed by attackers<sup>[3]</sup>**

[1] <https://opensea.io> [2] <https://metamask.io/>

[3] <https://www.zerofox.com/blog/flash-report-nft-drainer-claims-to-bypass-cryptocurrency-wallet-update/>

# Existing Countermeasures

- **The existing literature has not explored NFT drainers**
- Ethereum Phishing Scam Detection

Approach	Authors	Method	Publisher
Feature Based	Chen, Weili, et al. [1]	Ether features	2020 IJCAI
Graph Based	Wu, Jiajing, et al. [2]	Trans2Vec	2022 <i>IEEE Transactions on Systems, Man, and Cybernetics: Systems</i>
	Chen, Liang, et al. [3]	E-GCN	2020 ACM TOIT
	Li, Sijia, et al. [4]	TTAGN	2022 WWW

[1] Chen, Weili, et al. "Phishing Scam Detection on Ethereum: Towards Financial Security for Blockchain Ecosystem." *IJCAI*. 2020.

[2] Wu, Jiajing, et al. "Who are the phishers? phishing scam detection on ethereum via network embedding." *IEEE Transactions on Systems, Man, and Cybernetics: Systems* (2020).

[3] Chen, Liang, et al. "Phishing scams detection in ethereum transaction network." *ACM Transactions on Internet Technology (TOIT)* 21.1 (2020): 1-16.

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	Li, Sijia, et al. [4]	TTAGN	2022 WWW

**But they are difficult to apply to NFT phishing scam detection!**

[1] Chen, Weili, et al. "Phishing Scam Detection on Ethereum: Towards Financial Security for Blockchain Ecosystem." *IJCAI*. 2020.

[2] Wu, Jiajing, et al. "Who are the phishers? phishing scam detection on ethereum via network embedding." *IEEE Transactions on Systems, Man, and Cybernetics: Systems* (2020).

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# In this work

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Understand NFT drainer activity



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Understand NFT drainer activity



Insights

Design NFT drainer detection system



# Data Collection

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- Jan-01-2022 ~ Dec-31-2022
- NFT transaction data from Ethereum blockchain

Type	Value
NFT	80,795,833
Address	4,733,670
Transaction	127,820,930

- NFT drainer accounts from five channels
  - Drainer: an account that have at least one gifted-in NFTs among reported accounts
  - Chainabuse<sup>[1]</sup>, CryptoscamDB<sup>[2]</sup>, Etherscan<sup>[3]</sup>, ScamSniffer<sup>[4]</sup>, Twitter<sup>[5]</sup>
  - 1,135 accounts

[1] <https://www.chainabuse.com> [2] <https://www.cryptoscamdb.org> [3] <https://www.etherscan.io>  
[4] <https://www.scamsniffer.io> [5] <https://www.twitter.com>

# Data Collection

- Jan-01-2022 ~ Dec-31-2022
- NFT transaction data from Ethereum blockchain

To understand NFT drainer activity,

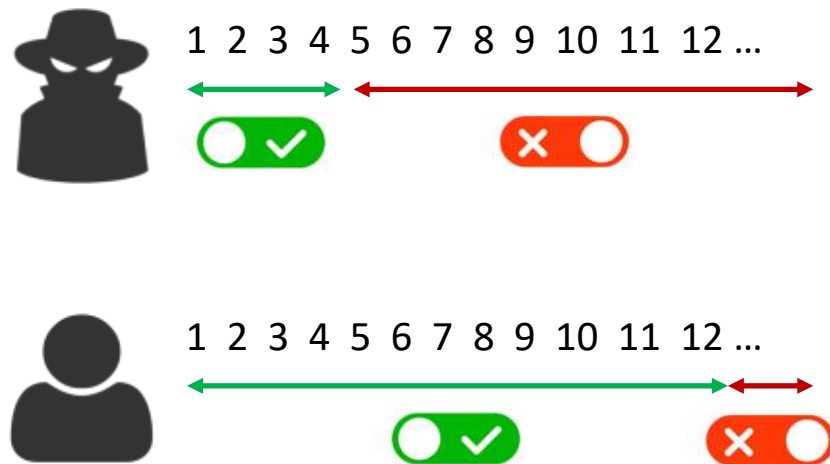
use NFT transaction data during Jan-01-2022 ~ Jul-31-2022  
including 645 drainer accounts

- NFT drainer accounts from five channels
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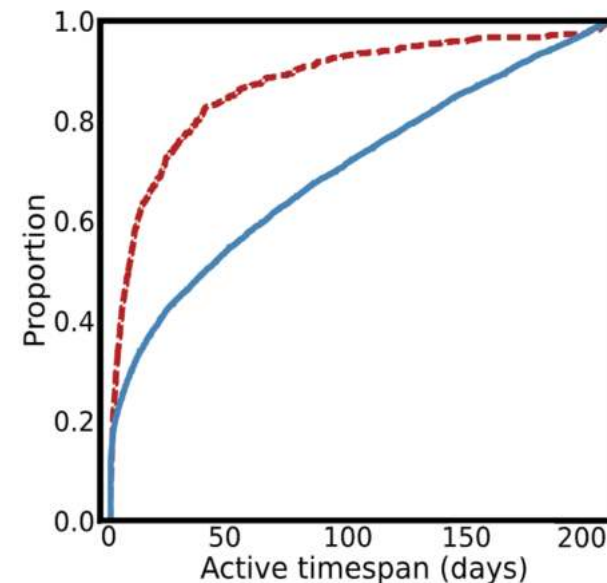
# Drainer Activity Characterization

## Trading Behavior

- Have a short active timespan
  - 60% of drainers have only 15 days or less of NFT trading activity
  - 60% of regular users have 67 days or less of NFT trading activity



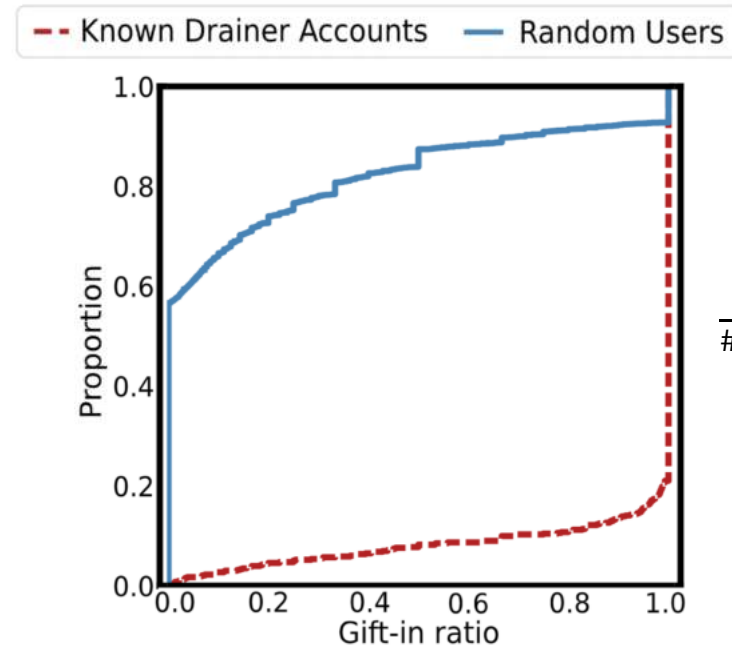
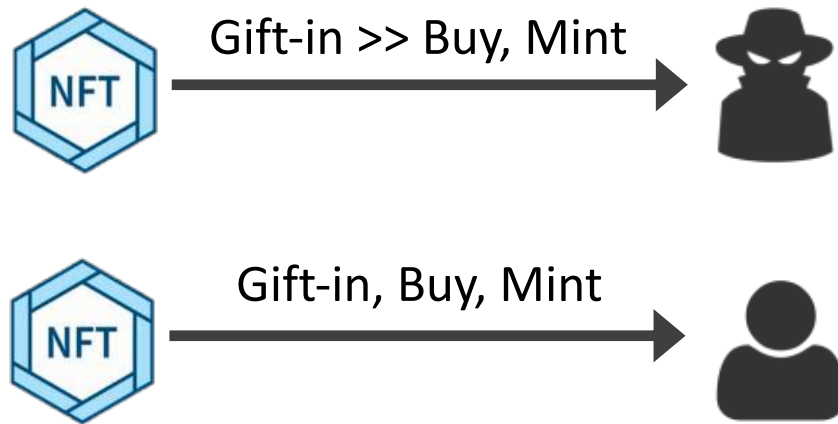
--- Known Drainer Accounts    — Random Users



# Drainer Activity Characterization

## Trading Behavior

- Acquire most NFTs from gift-ins
  - 80% of drainers acquired NFTs only through gift-ins
  - 8% of regular users acquired NFTs only through gift-ins



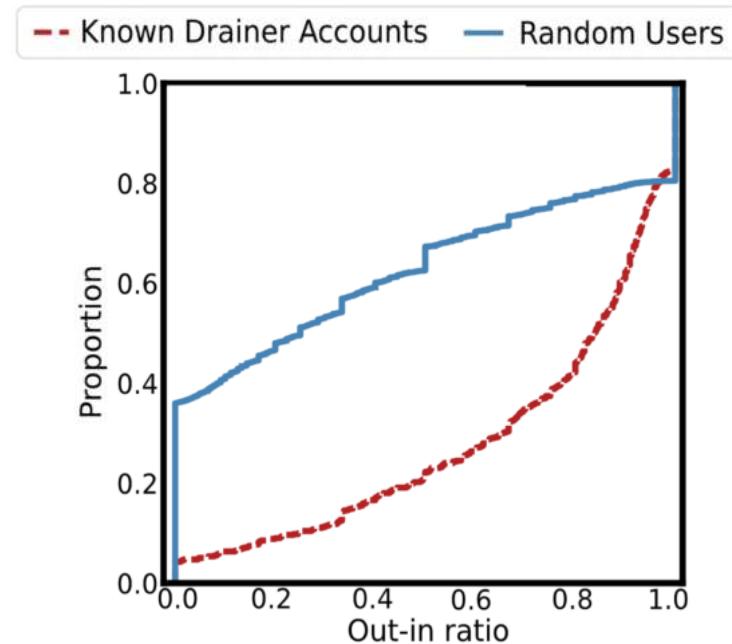
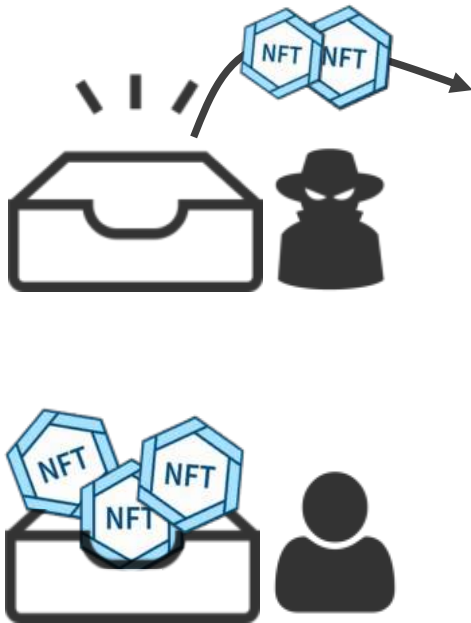
\*Gift-in ratio

$$\frac{\# \text{ NFTs from gift - in}}{\# \text{ NFTs from mint, buy, gift - in}}$$

# Drainer Activity Characterization

## Trading Behavior

- Sell or gift-out most of acquired NFTs
  - 76% of drainers transferred out more than half of their NFTs
  - 38% of regular users did not make any out-transactions at all




\*Out-in ratio

$$\frac{\# \text{ burn} + \# \text{ sell} + \# \text{ gift} - \text{out}}{\# \text{ mint} + \# \text{ buy} + \# \text{ gift} - \text{in}}$$

# NFT Drainer Detector: DRAINCLoG Overview

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Insights 

Drainers have unique {  
Trading behavior  
Social context  
NFT transaction context}



# NFT Drainer Detector: DRAINCLoG Overview

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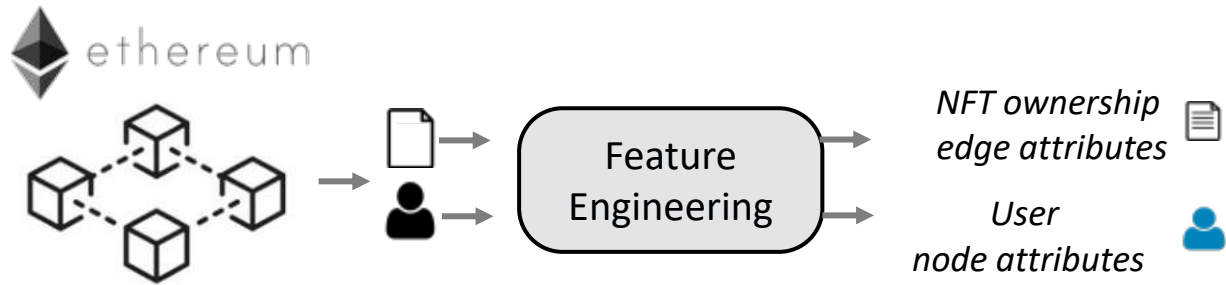


Design

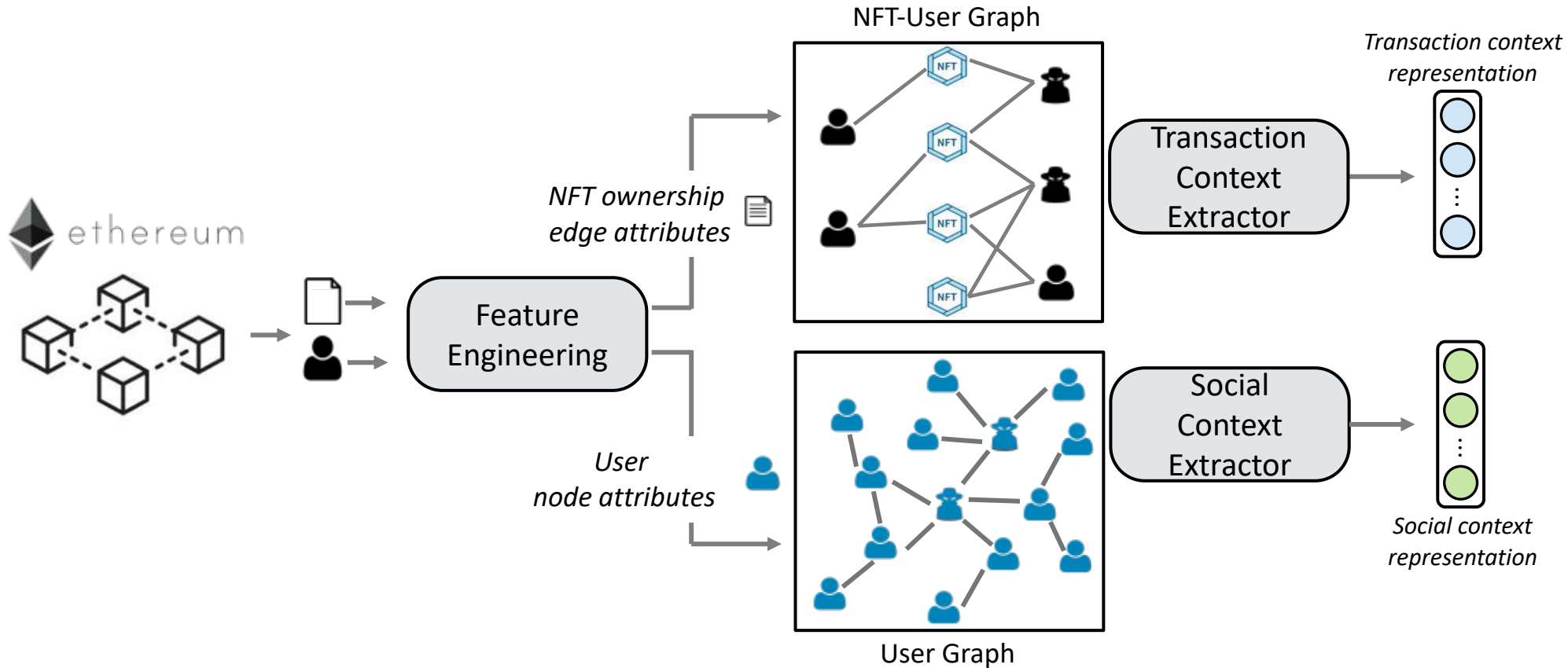
{  
Features  
Graphs  
GNNs  
}

# NFT Drainer Detector: DRAINCLoG Overview

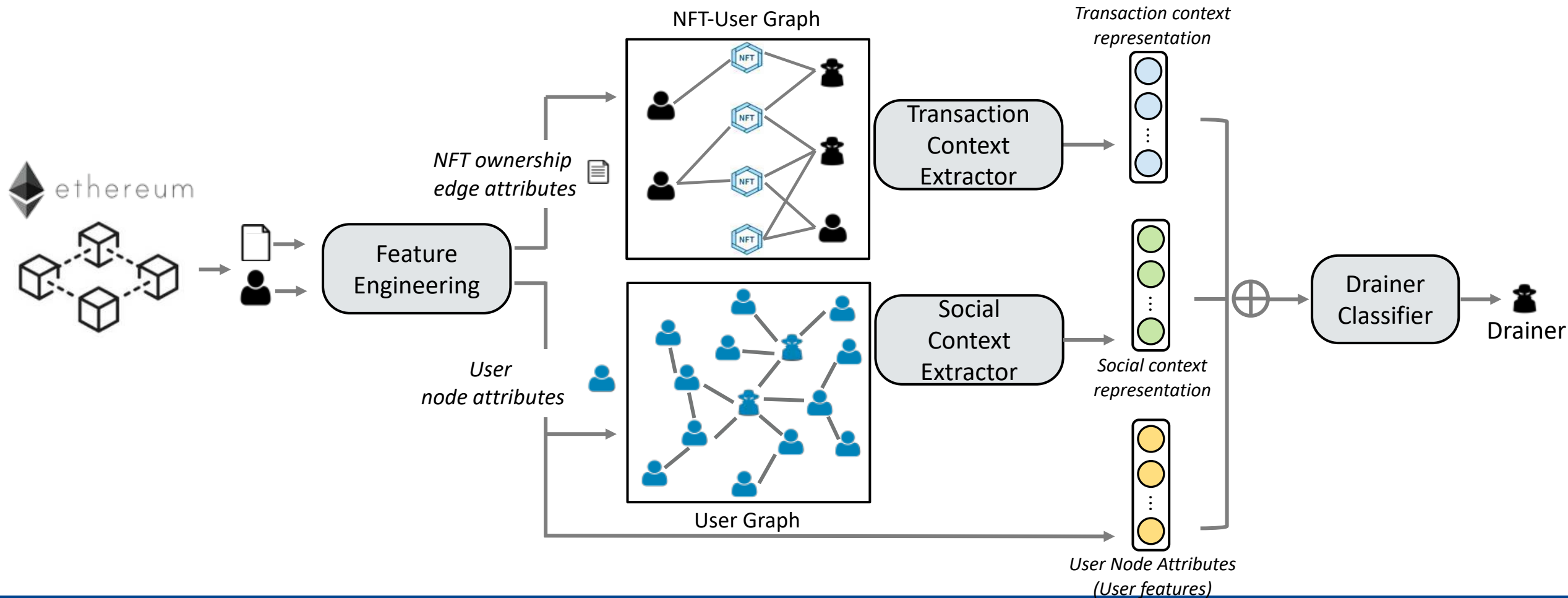
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# NFT Drainer Detector: DRAINCLoG Overview

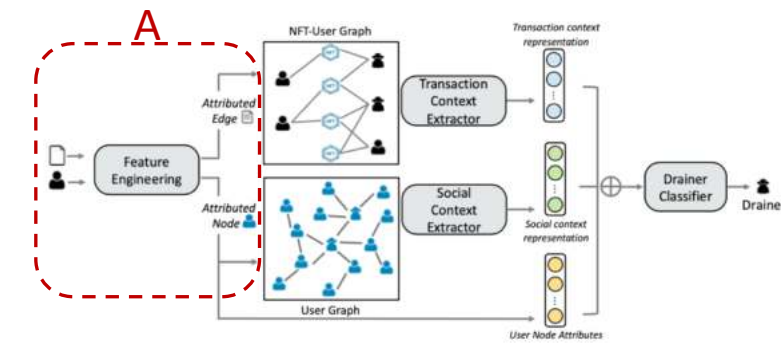


# NFT Drainer Detector: DRAINCLoG Overview



# NFT Drainer Detector Design

## A. Feature Engineering

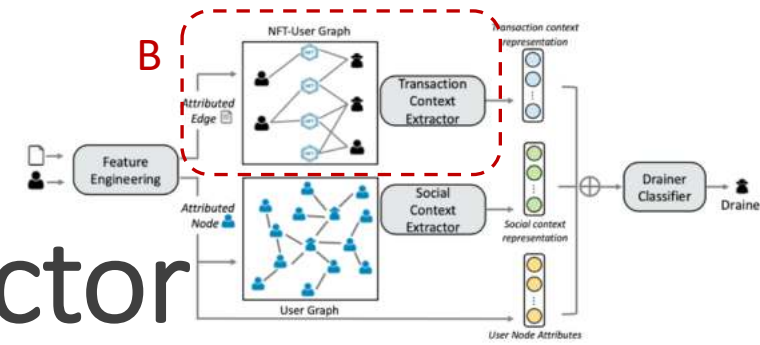


- **NFT ownership attributes**
  - Create representations of how users interact with NFTs
- **User attributes**
  - Create representations of their trading behaviors




NFT ownership attributes (7 dimensions)	User attributes (19 dimensions)
<ul style="list-style-type: none"> <li>▪ In-transaction type</li> <li>▪ Out-transaction type</li> <li>▪ In-price</li> <li>▪ Out-price</li> <li>▪ Holding time</li> <li>▪ Average holding time</li> <li>▪ Average sale price</li> </ul>	<ul style="list-style-type: none"> <li>▪ Number of each transaction type (5)</li> <li>▪ Number of collections for each transaction type (5)</li> <li>▪ Number of neighbors for each transaction type (4)</li> <li>▪ Frequency of gift-ins &amp; sales</li> <li>▪ Active timespan</li> <li>▪ Gift-in ratio</li> <li>▪ Out-in ratio</li> </ul>

# NFT Drainer Detector Design

## B. NFT Transaction Context Extractor

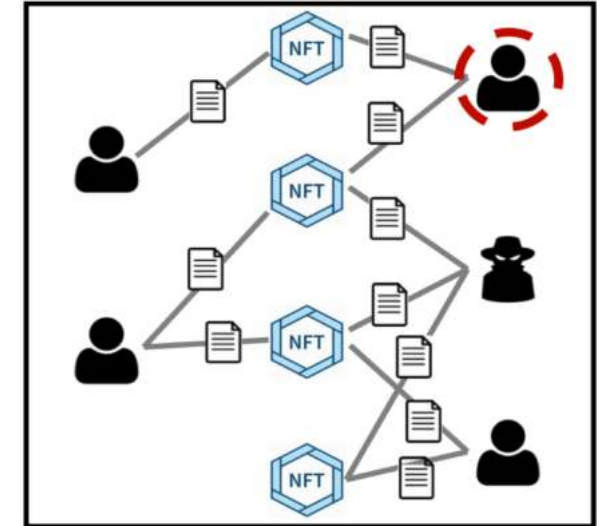


- **NFT-User graph Construction**

- Model ownership changes in NFTs
- Two types of *Nodes*: User , NFT 
- *Attributed Edge* 

- **NFT transaction context extraction**

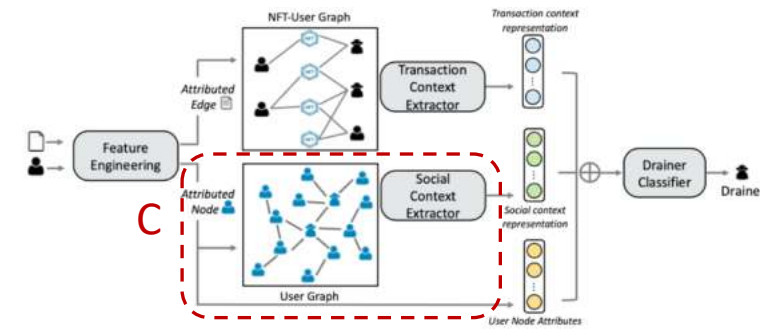
- Train a GNN on the graph
- $$h_u^U = \prod_{k=1}^K \sigma \left( \sum_{n' \in N(u)} [\alpha_{un'}]_k \cdot (W^U \cdot \text{concat}(t_{un'}, h_{n'}^N)) \right)$$
  
where 
$$h_{n'}^N = \sigma \left( W^N \cdot \text{aggregate}(t_{u_1}, t_{u_2}, \dots, t_{u_m}) \right)$$






NFT-User graph

# NFT Drainer Detector Design

## C. Social Context Extractor

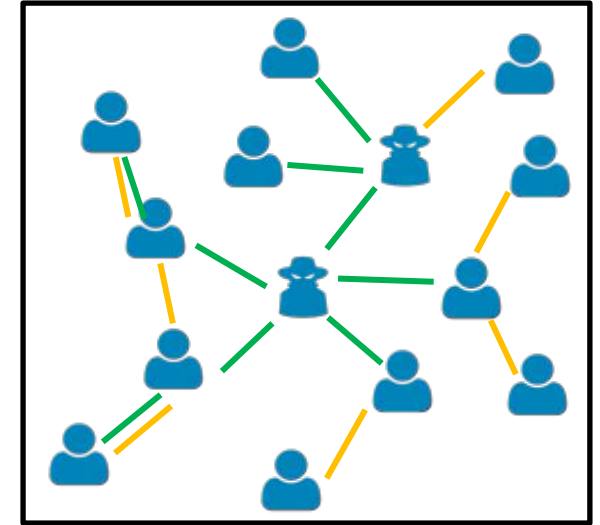


- **User graph Construction**

- Model user interactions
- One type of *Attributed Node*: User(Address) 
- Two types of *Edges*: Sale  , Gift 

- **Social context extraction**

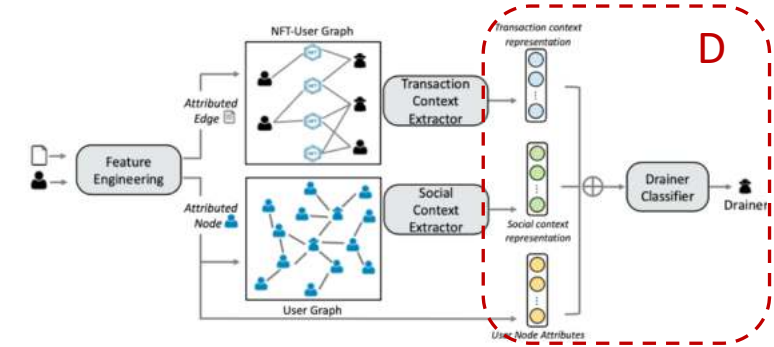
- Train a GNN on the graph
- Update node representations using R-GCN to consider edge types
- $$h_u^{l+1} = \sigma \left( W^l h_u^l + \sum_{r \in R} \text{AGG}_U \left( \frac{1}{c_{u,r}} W_r^l h_v^l \right), \forall v \in N(u)_r \right)$$
 (Relational-Graph Convolution Networks)



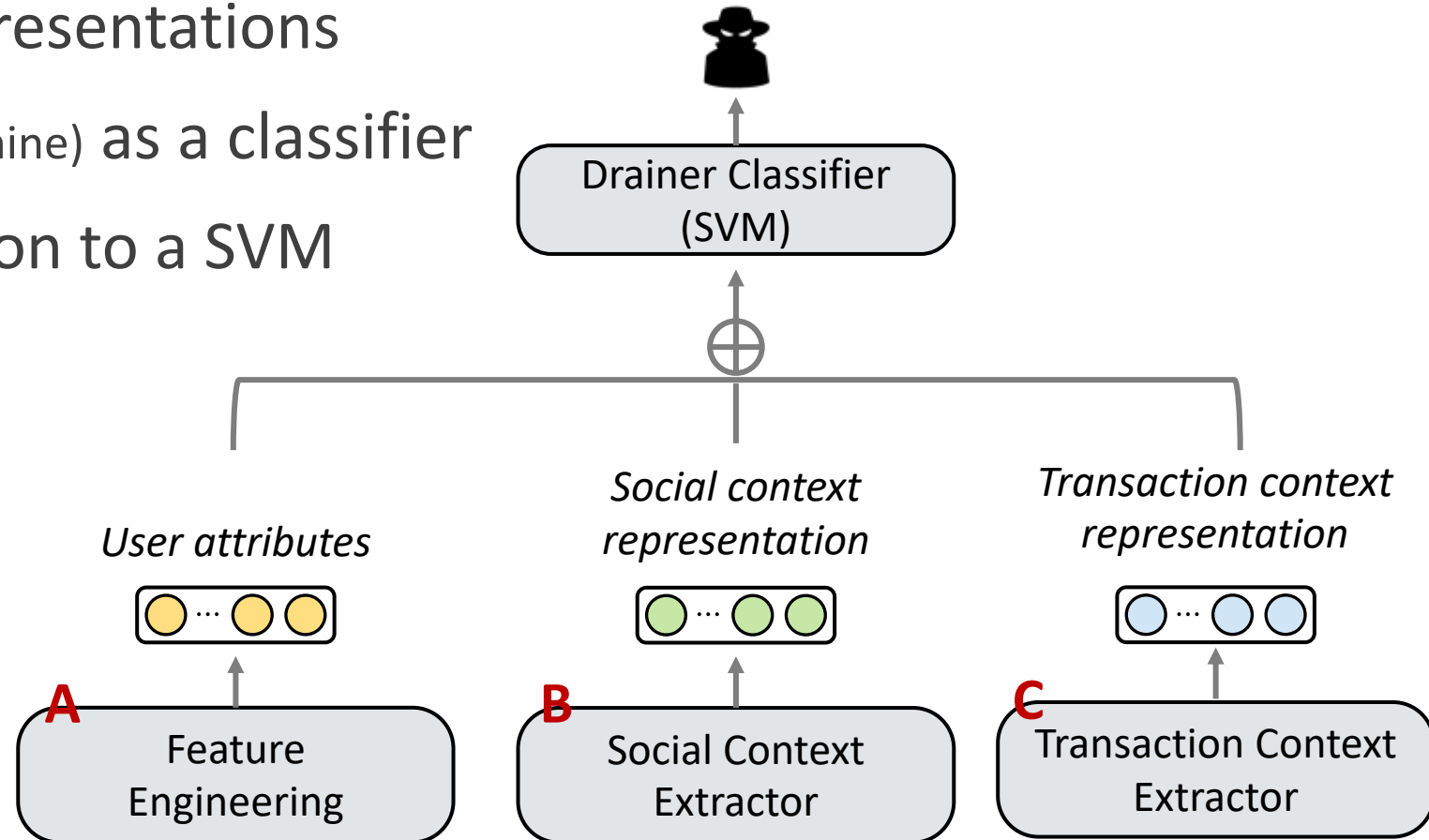
User graph

# NFT Drainer Detector Design

## D. Drainer Classifier



- Concatenate the three representations
- Use a SVM (Support Vector Machine) as a classifier
- Feed the final representation to a SVM





# Evaluation Dataset

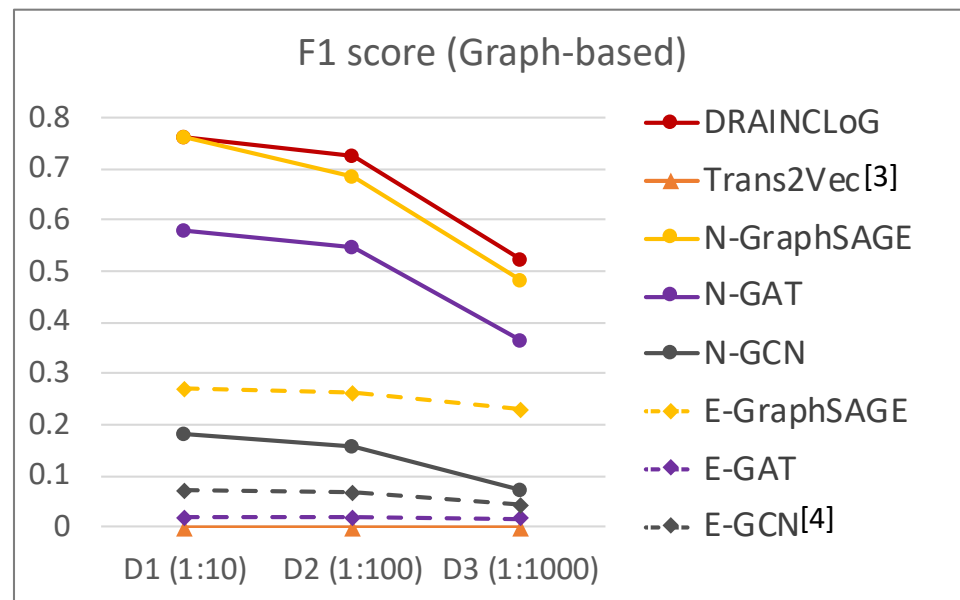
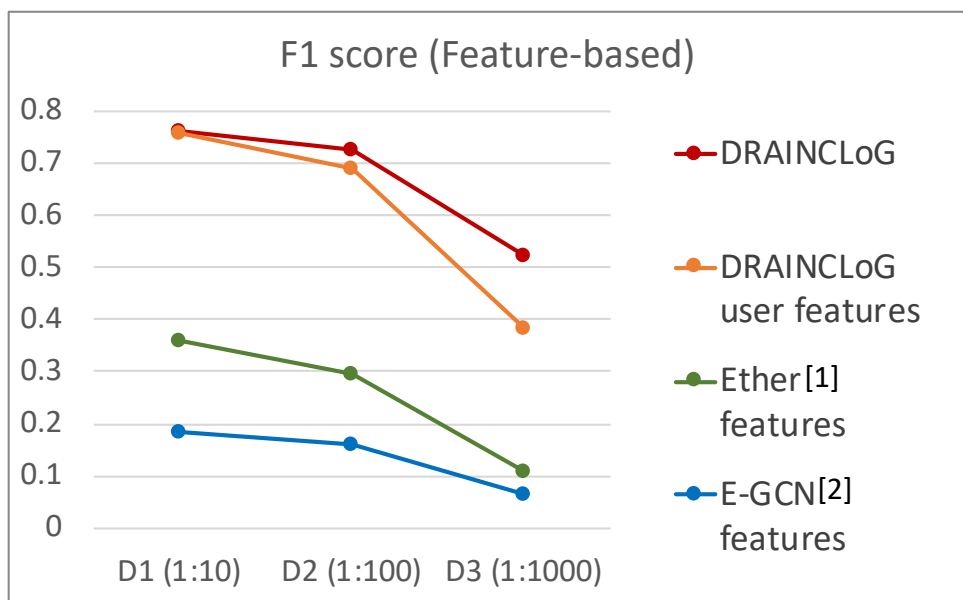
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- **Training:** Jan-01-2022 ~ July-31-2022
  - Drainers: 645
- **Evaluation:** Aug-01-2022 ~ Dec-31-2022
  - Drainers: 490

Dataset		Ratio	# central nodes	# total nodes	# transactions
Training	$D_0$	1:80	52,245	2,010,384.0	24,745,525.0
Evaluation	$D_1$	1:10	6,006	2,087,436.0	28,375,070.6
	$D_2$	1:100	55,146	2,743,003.4	41,384,504.8
	$D_3$	1:1000	546,546	3,179,105.4	45,289,602.6

# Evaluation

## Drainer Classification



[1] Chen, Weili, et al. "Phishing Scam Detection on Ethereum: Towards Financial Security for Blockchain Ecosystem." *IJCAI*. 2020.

[2] Chen, Liang, et al. "Phishing scams detection in ethereum transaction network." *ACM Transactions on Internet Technology (TOIT)* 21.1 (2020): 1-16.

[3] Wu, Jiajing, et al. "Who are the phishers? phishing scam detection on ethereum via network embedding." *IEEE Transactions on Systems, Man, and Cybernetics: Systems* (2020).

[4] Kipf, Thomas N., and Max Welling. "Semi-supervised classification with graph convolutional networks." *arXiv preprint arXiv:1609.02907* (2016).

[5] Veličković, Petar, et al. "Graph attention networks." *arXiv preprint arXiv:1710.10903* (2017).

[6] Hamilton, Will, Zhitao Ying, and Jure Leskovec. "Inductive representation learning on large graphs." *Advances in neural information processing systems* 30 (2017).

# Evaluation

# Robustness against Evasion Attack

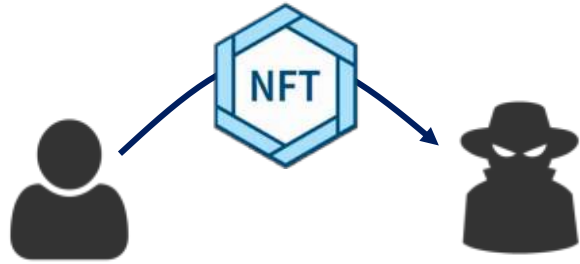
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- Assumptions
  - DRAINLoG monitoring system + Victim's reporting system
  - Detected drainers are immediately blocked their trading on marketplaces
  - To benefit from stolen NFTs, drainers have to quickly sell the NFTs at lower prices
- Attackers can modify their trading patterns to avoid detection
- Evaluate DRAINLoG's robustness under various attack scenarios

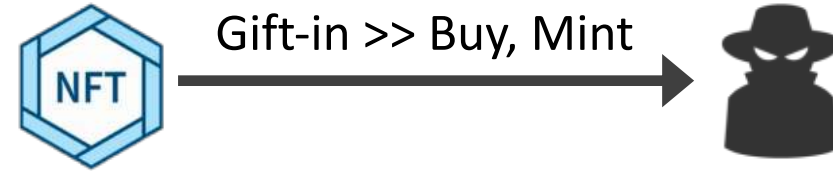
# Evaluation

## Robustness against Evasion Attack

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Draining NFTs records as gifts

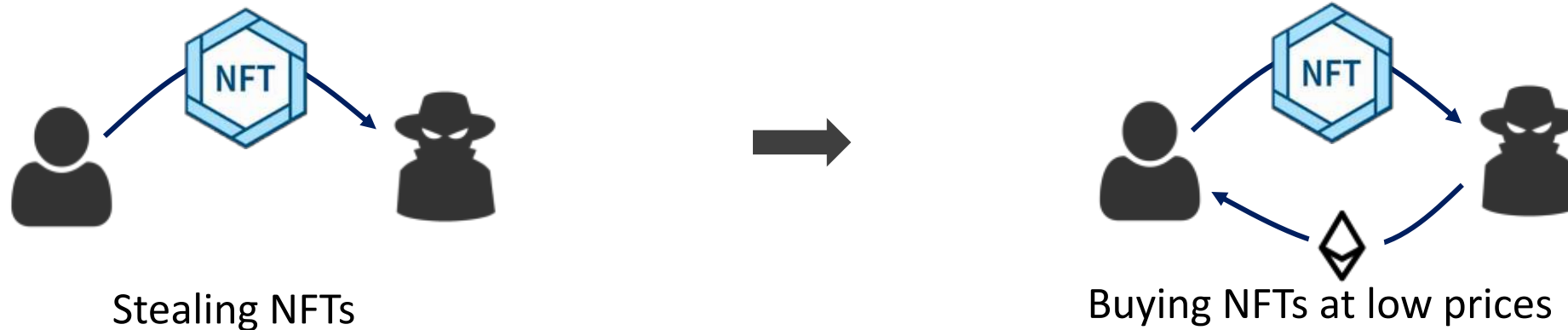


Acquire most NFTs through gift-ins

# Evaluation

## Robustness against Evasion Attack

Attack Scenario Example: Send a small amount of Ether to victim



For each attacker,  
Change  $L\%$  of *gifting-in transactions* to *buying transactions*  
by sending  $X\%$  of average sale price of each NFT to victims

$$L \in \{10, 30, 50\}, \quad X \in \{1, 10, 60\}$$

# Evaluation

## Robustness against Evasion Attack

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- Evasion attack results

Attack (L = 50)	D1 (1:10)			D2 (1:100)		
X	Pre.	Rec.	F1	Pre.	Rec.	F1
60	0.873	0.114	0.202	0.42	0.114	0.180
<i>Original Value</i>	<b>0.989</b>	<b>0.622</b>	<b>0.763</b>	<b>0.878</b>	<b>0.621</b>	<b>0.727</b>

# Evaluation

## Robustness against Evasion Attack

- Update DRAINCLoG by re-training only SVM classifier with additional 3% of attackers

Attack (L = 50)	D1 (1:10)			D2 (1:100)			D1 (1:10)			D2 (1:100)		
	Pre.	Rec.	F1	Pre.	Rec.	F1	Pre.	Rec.	F1	Pre.	Rec.	F1
X												
60	0.873	0.114	0.202	0.42	0.114	0.180	0.97	0.644	0.774	0.769	0.645	0.701
<i>Original Value</i>	<b>0.989</b>	<b>0.622</b>	<b>0.763</b>	<b>0.878</b>	<b>0.621</b>	<b>0.727</b>	<b>0.989</b>	<b>0.622</b>	<b>0.763</b>	<b>0.878</b>	<b>0.621</b>	<b>0.727</b>

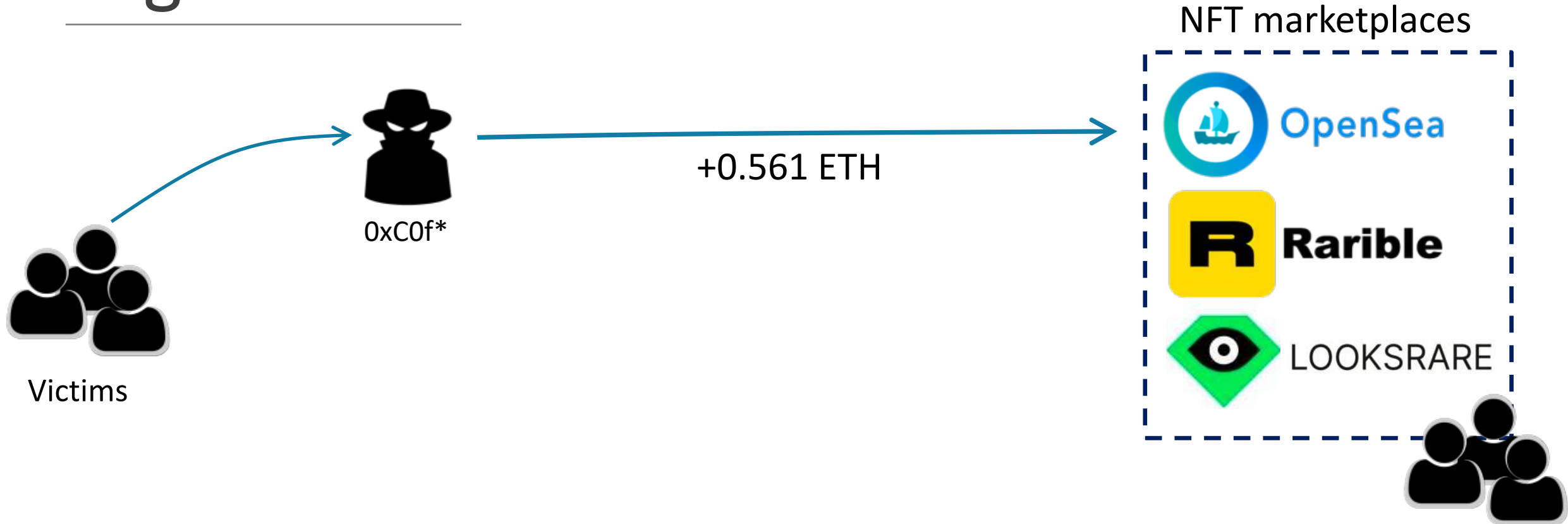
DRAINCLoG can effectively capture complex patterns of new drainers!

# Case Study

## High-Profile Attack

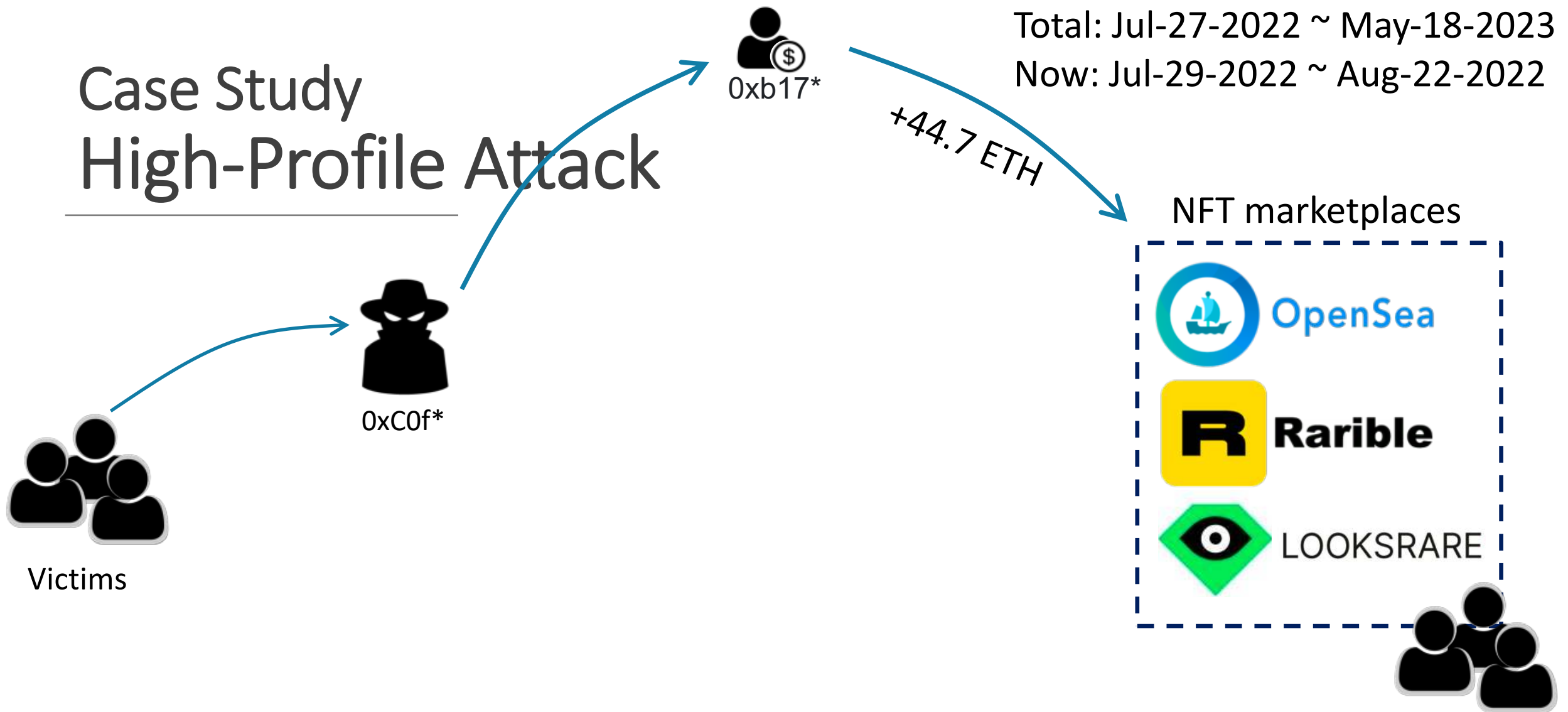
Total: Jul-27-2022 ~ May-18-2023

Now: Jul-27-2022 ~ Jul-28-2022

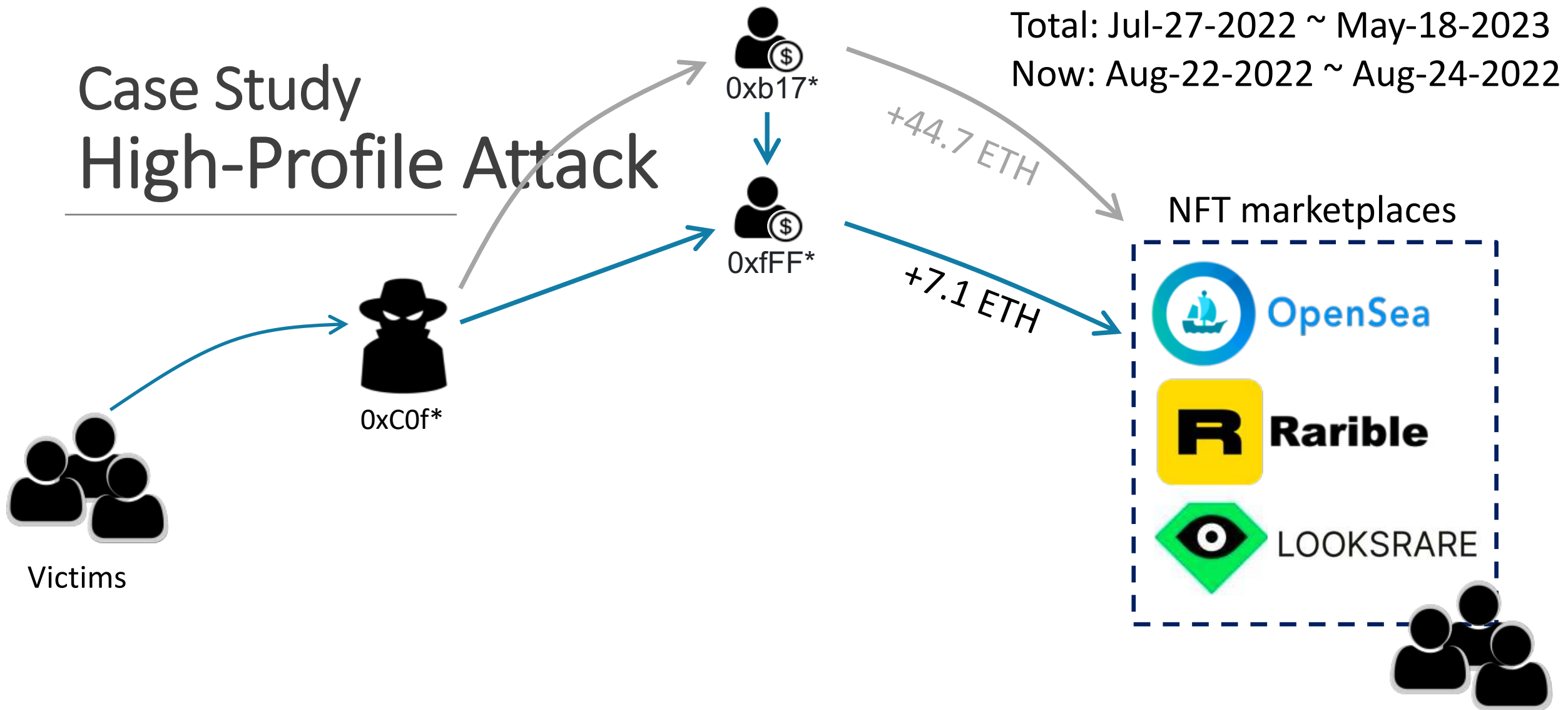




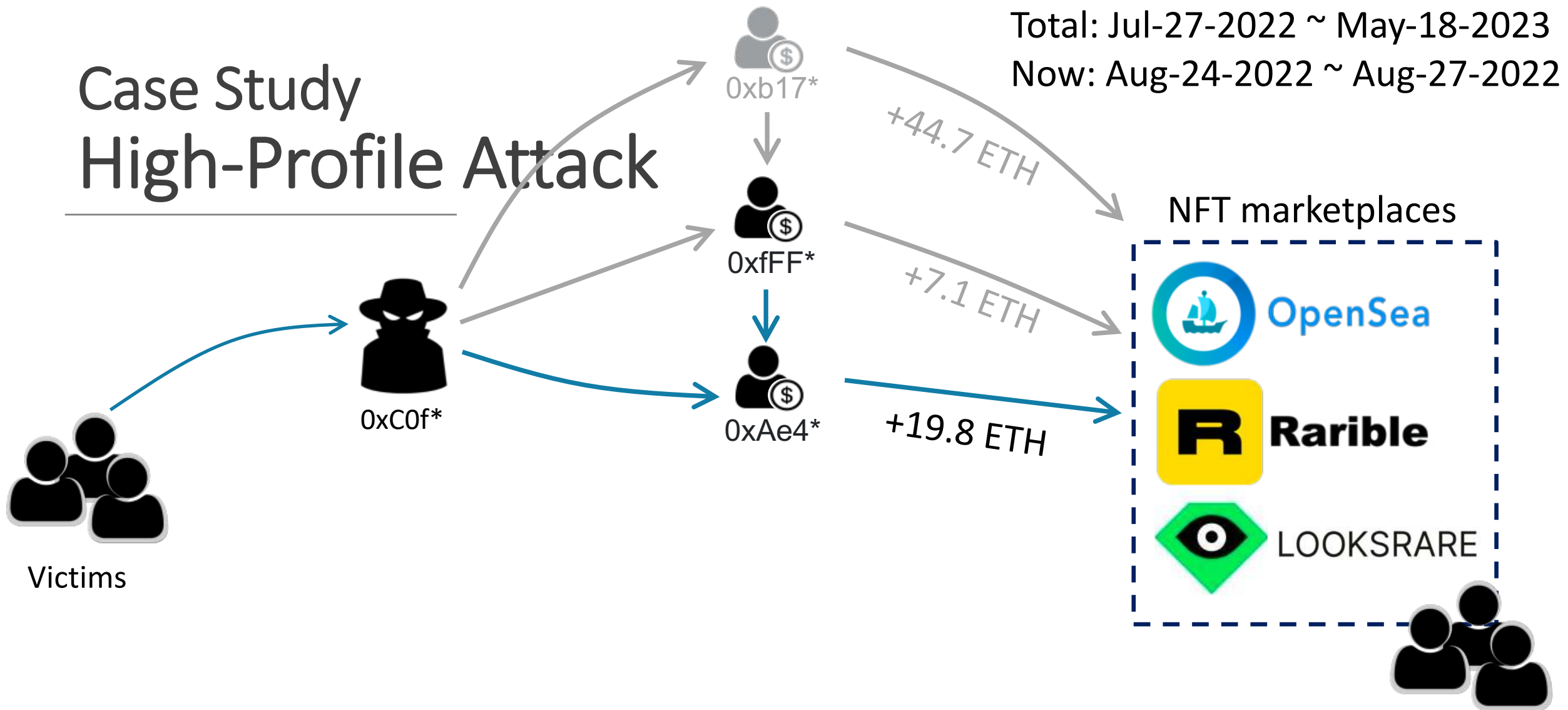
# Case Study High-Profile Attack



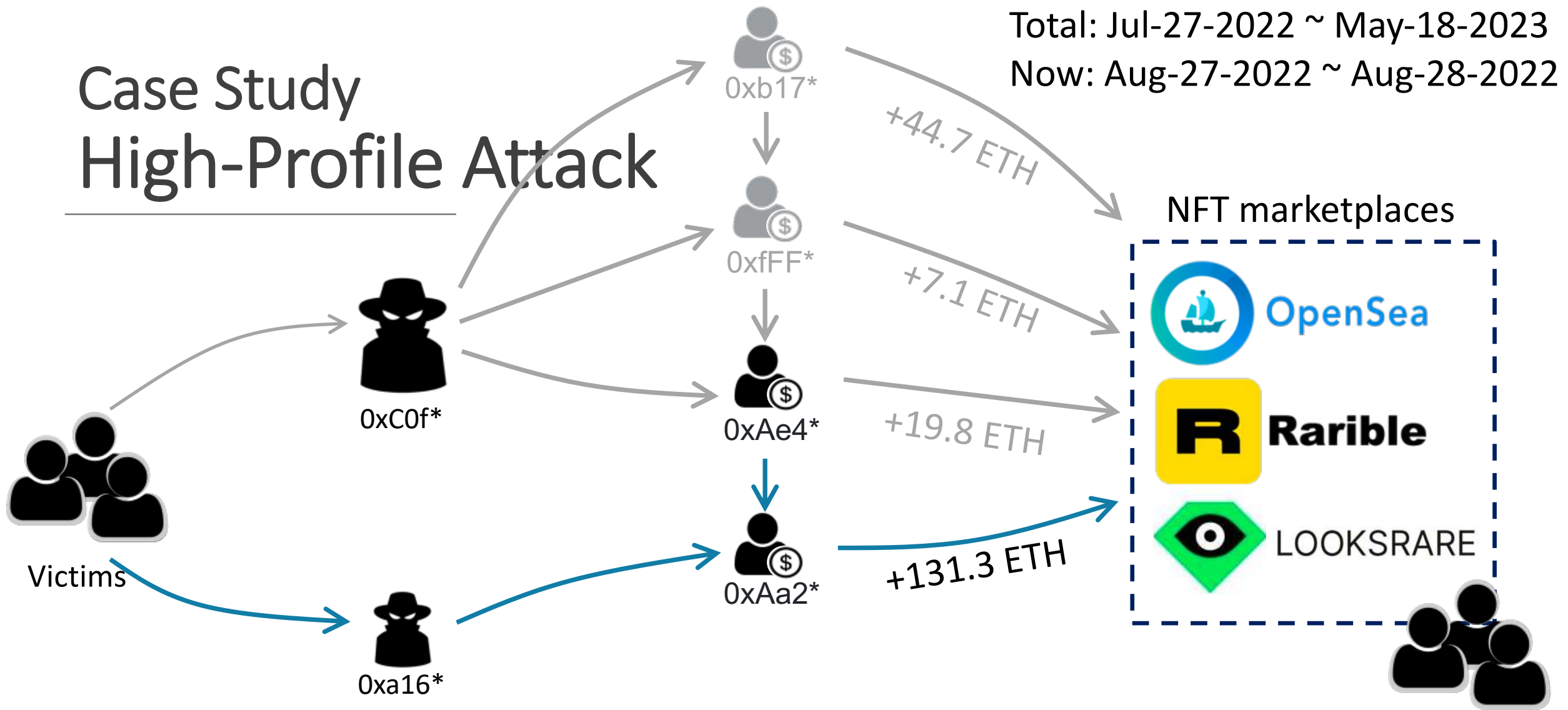
# Case Study High-Profile Attack



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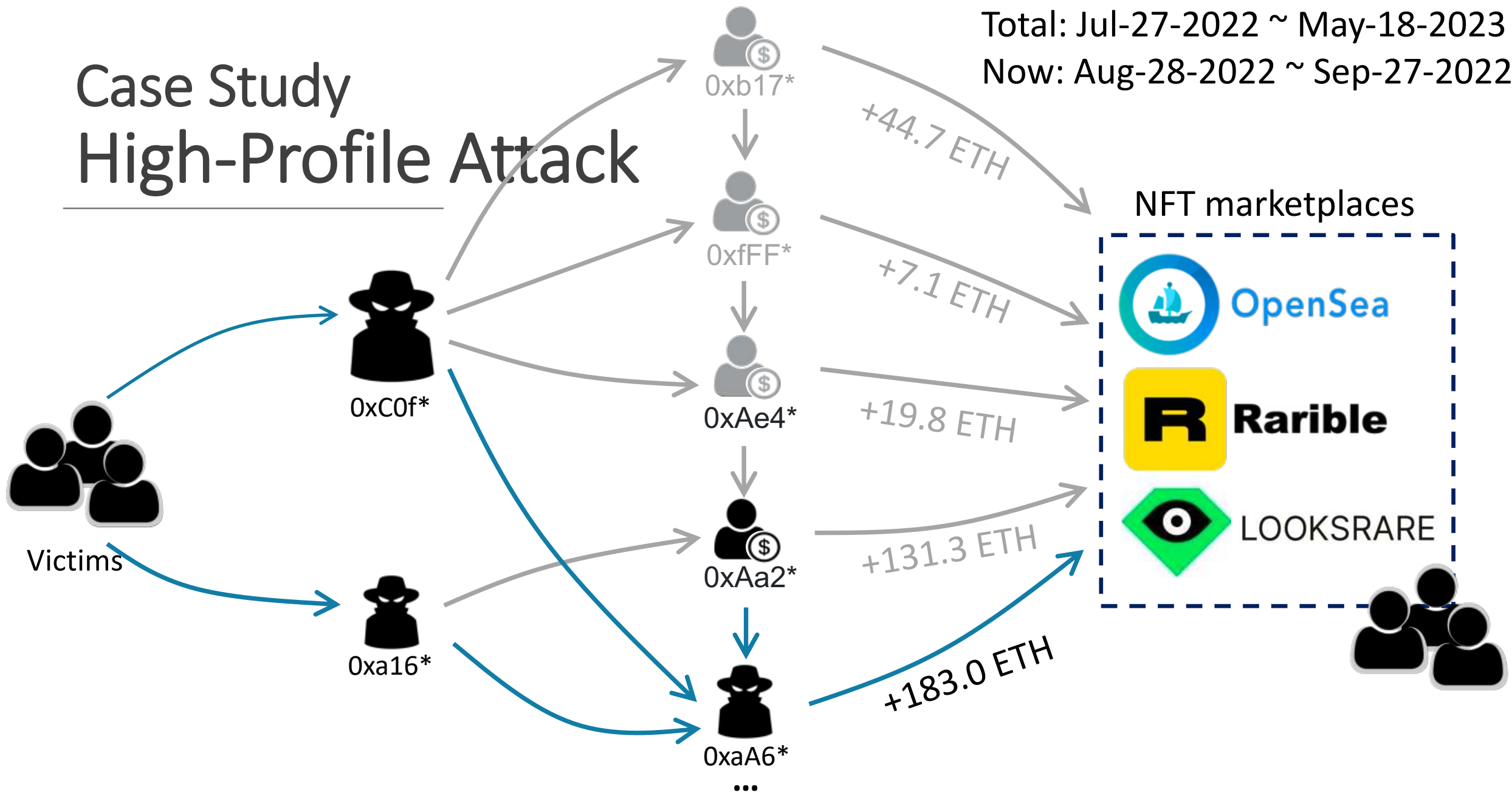


# Case Study High-Profile Attack



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Total: Jul-27-2022 ~ May-18-2023  
Now: Aug-28-2022 ~ Sep-27-2022



# Conclusion

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- NFT phishing scams are a significant threat to the NFT ecosystem
- However, the existing literature has not explored NFT drainers
- **DRAINCLoG:** Detecting Rogue Accounts with Illegally-obtained NFTs using Classifiers Learned on Graphs
  - The first study on NFT phishing scammers (drainers)
  - Conduct an in-depth study on NFT drainers
  - Propose a detection system, *DRAINCLoG*, and verify its effectiveness and robustness

# Thank you

Please feel free to contact me regarding our research.

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# Evaluation

## Drainer Classification

Model	Dataset (# drainer : # regular)	D1 (1:10)				D2 (1:100)				D3 (1:1000)			
		Metrics	Pre.	Rec.	F1	FP/TP	Pre.	Rec.	F1	FP/TP	Pre.	Rec.	F1
Feature based	<i>Ether features</i>	0.875	0.227	0.361	15.9/111.1	0.429	0.227	0.297	148.0/111.2	0.072	0.227	0.109	1433.2/111.2
	<i>E-GCN features</i>	0.838	0.104	0.185	10.0/51.0	0.334	0.104	0.159	102.4/51.0	0.047	0.104	0.064	1045.4/51.0
	<i>DRAINLoG user features</i>	0.976	0.618	0.757	7.4/302.4	0.779	0.618	0.689	86.2/304.2	0.277	0.627	0.385	801.8/307.2
Graph based	<i>E-GCN</i>	0	0	0	0.0/0.0	0	0	0	0.0/0.0	0	0	0	0.0/0.0
	<i>E-GAT</i>	0.832	0.037	0.071	3.7/18.1	0.349	0.037	0.067	33.6/18.0	0.055	0.037	0.044	311.5/18.1
	<i>E-GraphSAGE</i>	0.933	0.01	0.02	0.4/5.0	0.825	0.01	0.02	1.2/5.0	0.256	0.009	0.018	12.8/4.4
	<i>N-GCN</i>	0.98	0.157	0.271	1.6/77.0	0.867	0.157	0.265	12.0/77.2	0.435	0.157	0.231	99.9/76.9
	<i>N-GAT</i>	0.838	0.103	0.183	9.8/50.2	0.351	0.103	0.159	93.8/50.6	0.057	0.102	0.073	825.5/50.0
	<i>N-GraphSAGE</i>	0.982	0.411	0.58	3.8/201.4	0.811	0.411	0.546	47.4/202.6	0.323	0.415	0.363	426.3/203.4
<b><i>DRAINLoG</i></b>		<b>0.987</b>	<b>0.569</b>	<b>0.722</b>	<b>3.6/278.4</b>	<b>0.86</b>	<b>0.569</b>	<b>0.685</b>	<b>45.8/280.2</b>	<b>0.416</b>	<b>0.579</b>	<b>0.484</b>	<b>398.3/283.7</b>



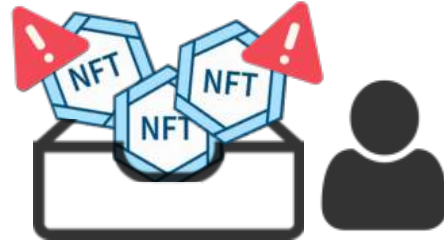
# Evaluation

## Identify potential Drainers

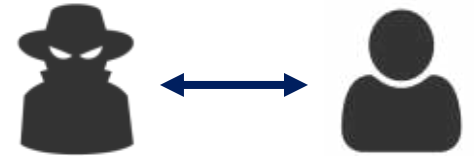
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- Verify false positives

- ✓ Possess suspicious NFTs



- ✓ Have a persistent relationship with reported phishing accounts



- ✓ Newly reported after 2022



- Identify 115 potential drainers among 379 false positives

# Appendix Ablation Study

- Analyze how each component affects performance
- Conduct the same detection task after eliminating each
  - User attributes (from Feature Engineering)
  - Social context
  - NFT transaction context
  - Edge types in User graph

