

NFT Wash Trading - Quantifying suspicious behavior in NFT markets

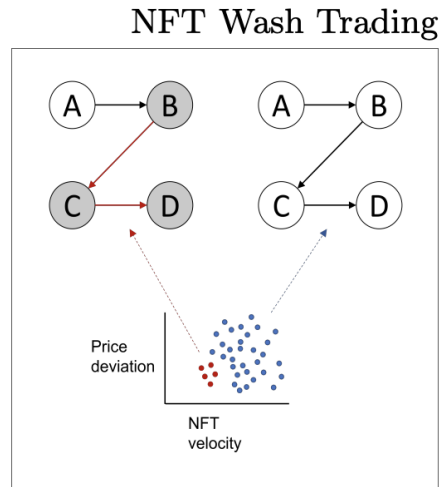
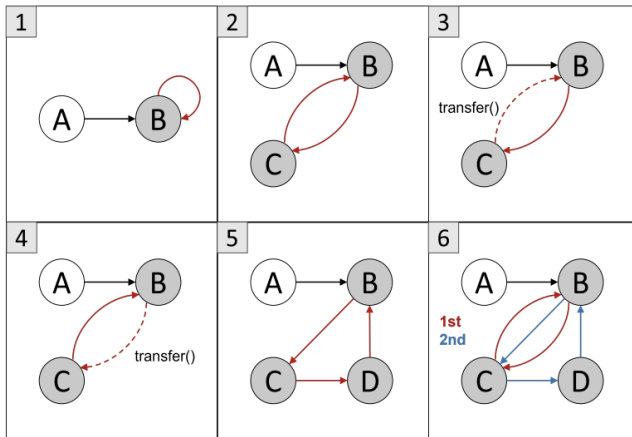
Intro:

- A non-fungible token (NFT) is a unique digital representation of physical or digital asset.
 - Applications such as designating ownership of assets like domain name registrations, most recognized use of NFTs currently is through representation and trade of digital art and collectibles. (like bored apes, cryptopunks, Jack Dorsey's first tweet, etc.)
 - People can own, trade and transfer NFTs which has led to the emergence of NFT markets (like OpenSea), where primary and secondary trades of such assets are facilitated.
- Smart contracts enable anonymous parties to carry out transactions without the need for intermediary, legal or external enforcement mechanisms, which enable users to sell/purchase NFTs by fixed prices or auctions.
 - As NFTs have been growing in pop culture (celebrities buying and popularizing specific NFT collections, rappers minting and selling their own NFT collections, luxury brands selling NFTs, etc), trade volumes have seen drastic growth from \$12M settled in September 2020 to volumes exceeding \$3.5B in September 2021. (surge of over 29,060%)
- Users connect to NFT marketplaces using public-key cryptography, which anonymizes user identities, and thus there is no theoretical limit to how many anonymous addresses a single user can control for trading NFTs.
 - Likely that there is a mixture of manual trading and bots that trade NFTs in clusters of addresses in their control to artificially inflate the trade volume and prices of NFTs, creating a false impression to uninformed traders of the NFT's value and popularity.
- This paper aims to address the following question: **'To what extent does wash trading occur in smart contract-based NFT markets on Ethereum, and to which extent does this practice distort prices?'**
 - "Conceptualizing trading patterns as a graph and proposing two detection algorithms, we identify 2.04% as the lower bound of suspicious sale transactions that closely follow the general definition of wash trading."

Methodology:

- "Due to the strict ordering of transactions and unique properties of NFT markets, blockchain transaction data presents a powerful and unique opportunity for pattern detection utilizing graph-based algorithms and address clustering"
- Building Transaction Graphs:
 - Transaction history of each NFT modelled as a directed multigraph $G_{nft} = (N, E)$, where N is the set of addresses and E is the set of transactions between addresses
 - The direction of the edges is given by the transaction flow from sender to receiver

- The weight of the edges represents the USD price at the time of the transaction
- Want to identify of clusters in which a sequence of transactions leads to no apparent position change for any of the addresses involved (closed cycles)
 - Used Deep-First-Search-Algorithm to identify closed cycles within the data set.
 - Adjusted algorithm using the temporal distance between transactions to detect sub-cycles.
 - Algorithm has a linear time complexity of $O((n + e)(c + 1))$ for n nodes (addresses), e edges (transactions) and c cycles
 - Below on LEFT are examples of suspicious transactions:
 - Red = suspicious cycle, Grey = potentially colluding addresses, solid lines = sales, dotted lines = transfers
 - RIGHT Figure = Detection of suspicious activity through a rapid sequence of transactions (<12 hrs) without taking market risk.



Results:

Suspicious addresses/transactions identified:

	Dataset	Identified	Percentage
Addresses	459,954	18,117	3.93%
Transactions	1,779,380	36,385 (cyclic: 30,467 sequential: 5,918)	2.04%
Volume in \$	6.9 b	149.5 m	2.17%
NFTs	3,572,483	16,289	0.45%

- Adversarial agents tend to target specific NFT collections for illicit transactions
- 60.6% of the identified clusters are simple variations with two transactions
 - Complex variations of three (8.7%) or more than three transactions are less common (30.7%). However, we find no signs of self-directed trades. Cyclical patterns are conducted at relatively rapid intervals.

- Overall, 48.1% of the identified cycles happen within a single day. 13.2% happen within one to seven days and 13.0% are just below 30 days.
- Peak suspicious activity tends to happen within the first $\frac{1}{3}$ of a collection's lifetime, possibly to raise initial awareness (hype) to attract buyers
- Find that the subsequent sale after a detected wash trade has, on average, an increased price of 30.53%
 - Despite this, age of the collection and consumer sentiment seem to be driving factors for NFT prices rather than wash sales

Algorithm 1 The detection algorithm

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1: Input:  $T$  timestamped blockchain transactions
2:  $L \leftarrow$  empty list of cycles
3: for  $nft \in T$  do
4:    $G_{nft} \leftarrow (N, E)$ 
5:    $G_{nft} \leftarrow$  identifier, weight
6:   label  $n \in N$  as discovered
7:   for all directed  $E$  of  $n$  do
8:     test for adjacent edges  $m$ 
9:     if  $m$  is not labeled as discovered then
10:      continue
11:    else
12:       $L \leftarrow cycle$ 
13:       $G_{nft}^* \leftarrow G_{nft} - E$ 
14:      break and recurse
15:    end if
16:  end for
17: end for
18: return  $L$ 

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