



NFTDisk: Visual Detection of Wash Trading in NFT Markets



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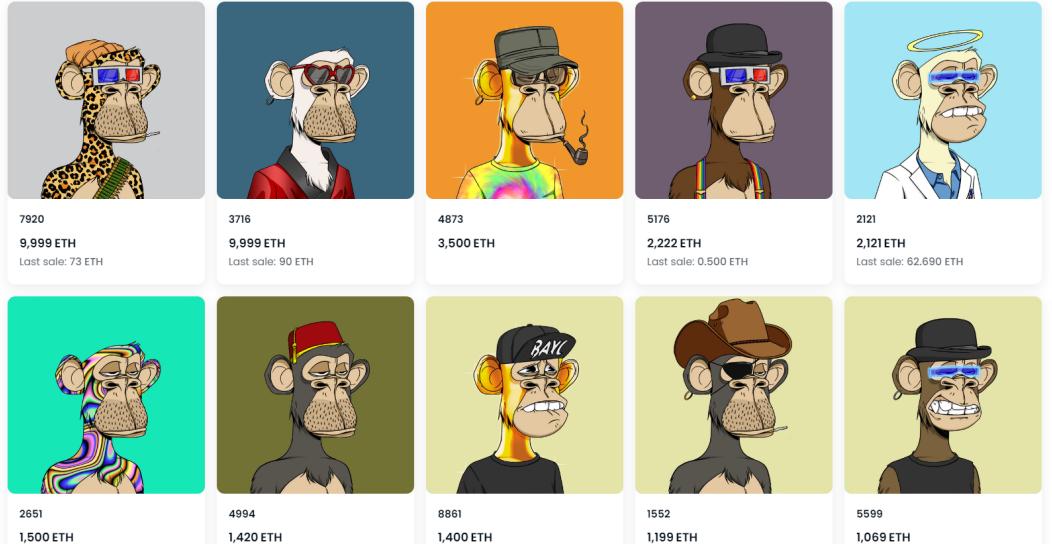
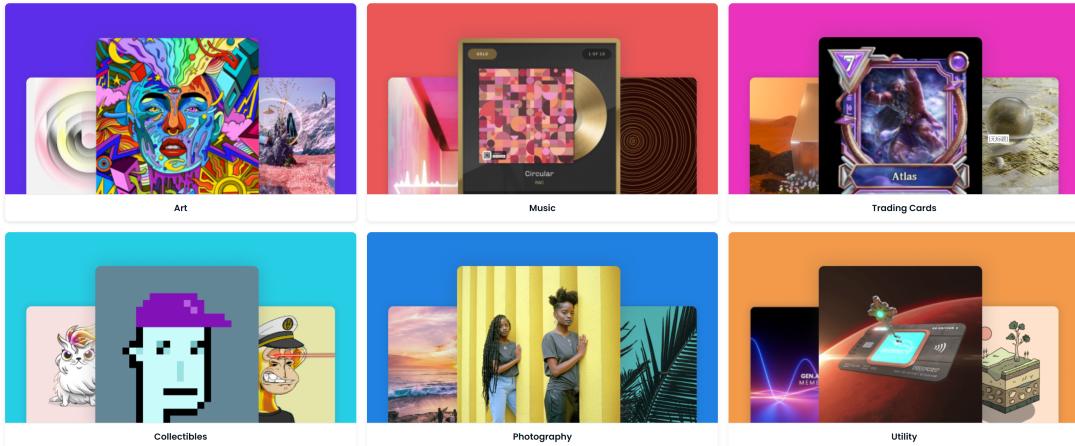
SINGAPORE
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Background

NFT (Non-Fungible Token)



NFT Investors



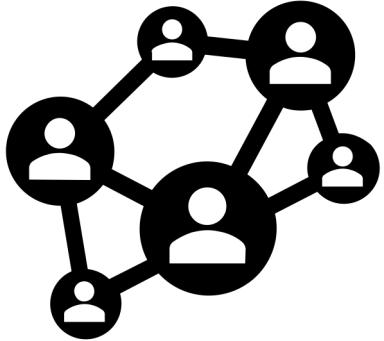
NFT Markets



Fraudulent Activities

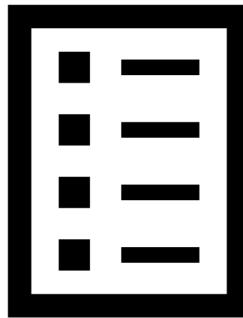
Background

Wash Trading



Colluding Addresses

→
Create



Fake Trade Volumes

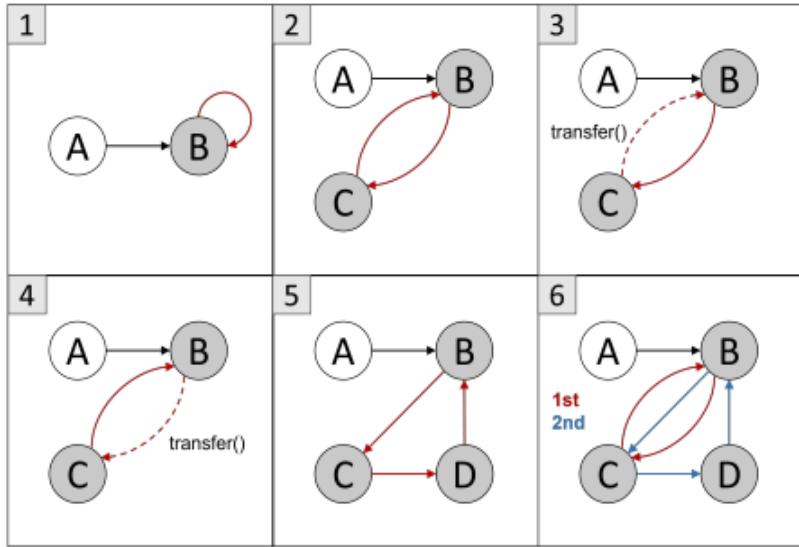
→
Mislead



NFT Investors

Motivation

Automatic Detection^[1]

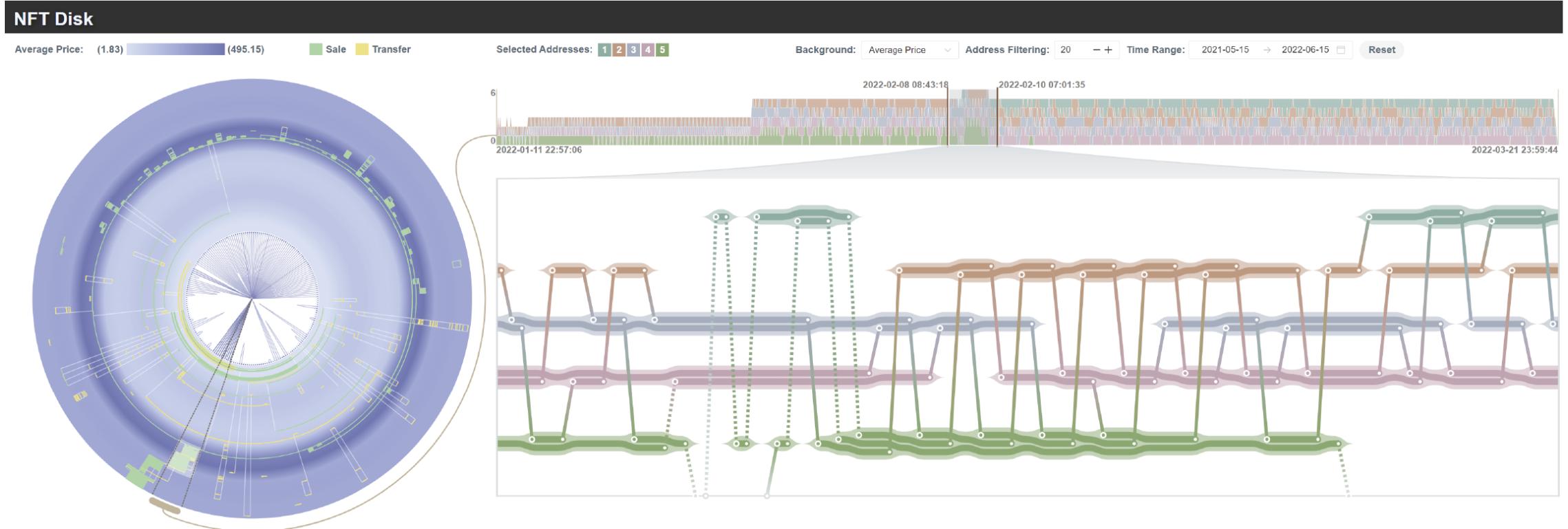


Manual Inspection

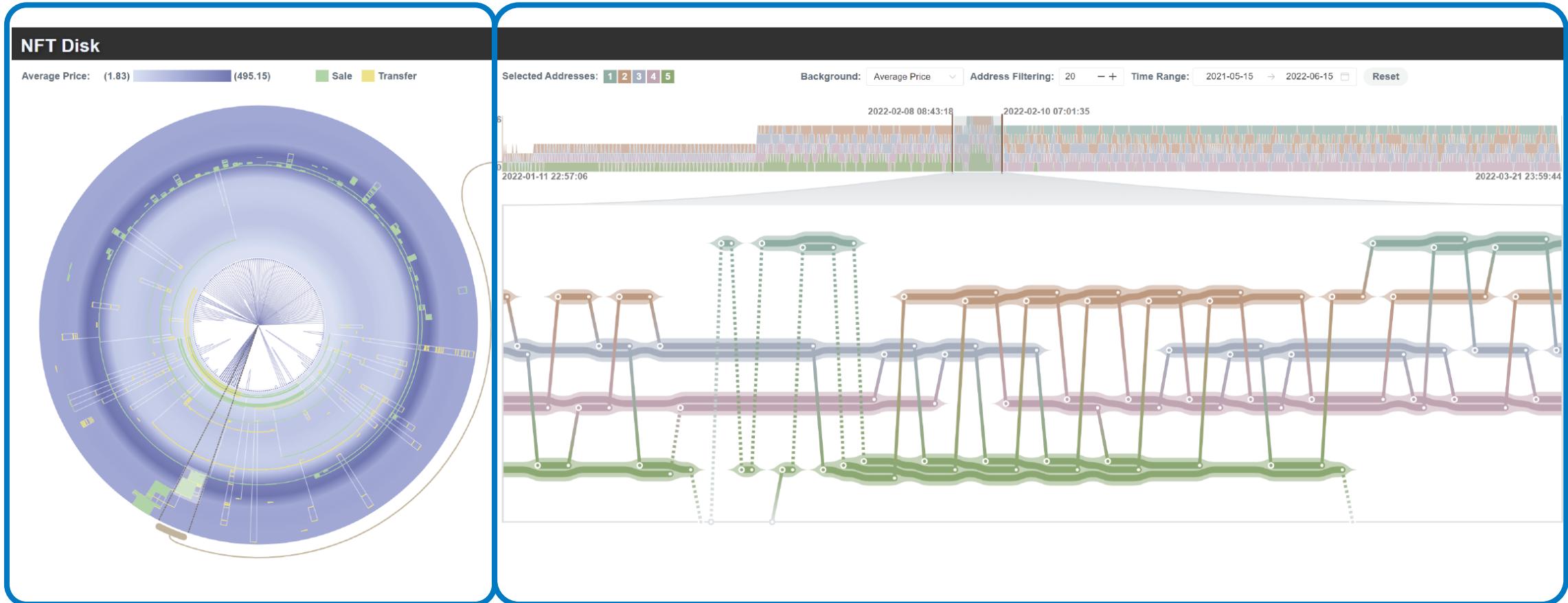
Token	Asset Id	Image	Seller	Buyer	Price (USD)	Token Price	Sale Date
RARI	2732				\$3,414.885	14.55 (ETH)	~11 days ago 7/19/2020, 1:26:36 PM
RARI	2732				\$3,755.2	16 (ETH)	~11 days ago 7/19/2020, 1:25:26 PM
RARI	2732				\$3,755.2	16 (ETH)	~11 days ago 7/19/2020, 1:22:44 PM
RARI	2732				\$3,755.2	16 (ETH)	~11 days ago 7/19/2020, 1:19:24 PM
RARI	2730				\$9,868.32	42 (ETH)	~11 days ago 7/19/2020, 1:02:11 PM
RARI	2730				\$8,928.48	38 (ETH)	~11 days ago 7/19/2020, 12:58:25 PM
RARI	2730				\$8,928.48	38 (ETH)	~11 days ago 7/19/2020, 12:56:16 PM
RARI	2730				\$4,699.2	20 (ETH)	~11 days ago 7/19/2020, 12:53:25 PM

- **Automatic Detection** can only find a subset of wash trading due to their sophisticated patterns.
- **Manual Inspection** is usually required, but it is hard to get useful information directly from the original transactions.

[1] von Wachter V, Jensen J R, Regner F, et al. NFT Wash Trading: Quantifying suspicious behaviour in NFT markets[J]. arXiv preprint arXiv:2202.03866, 2022.

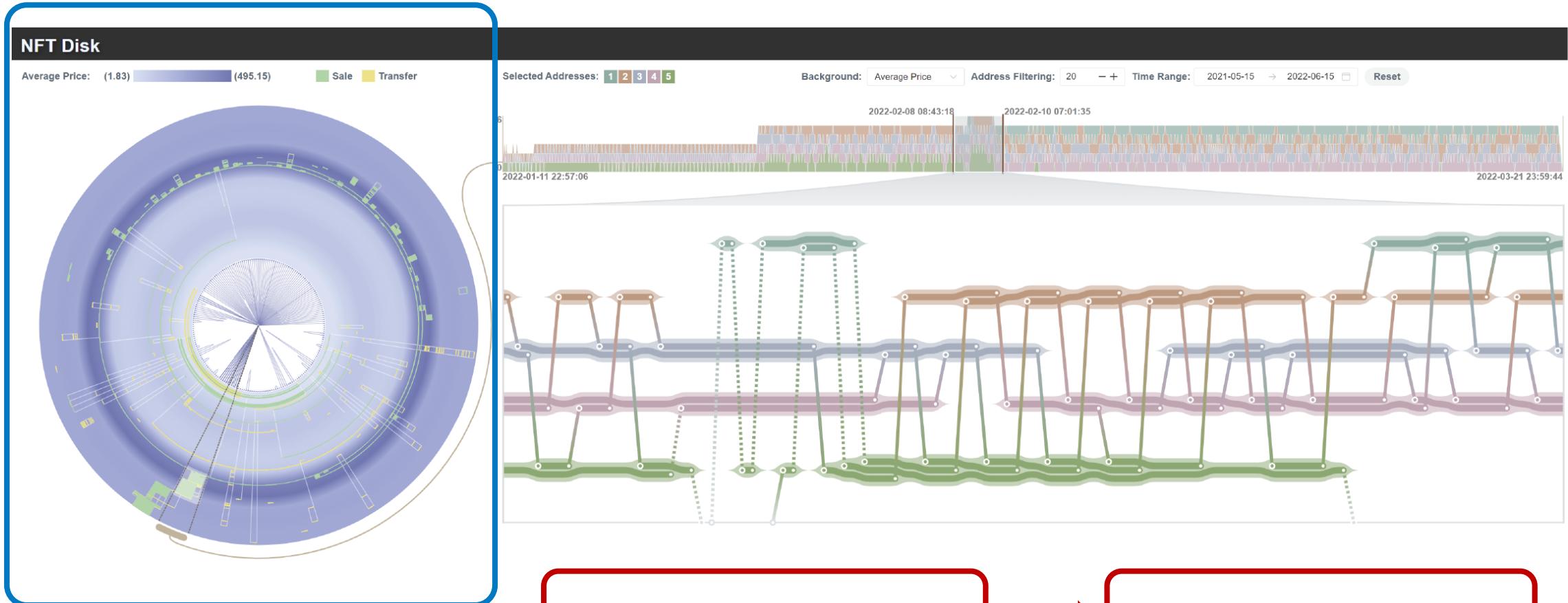


NFTDisk: a novel visualization for investors to visually identify wash trading activities in NFT markets.



Disk Module

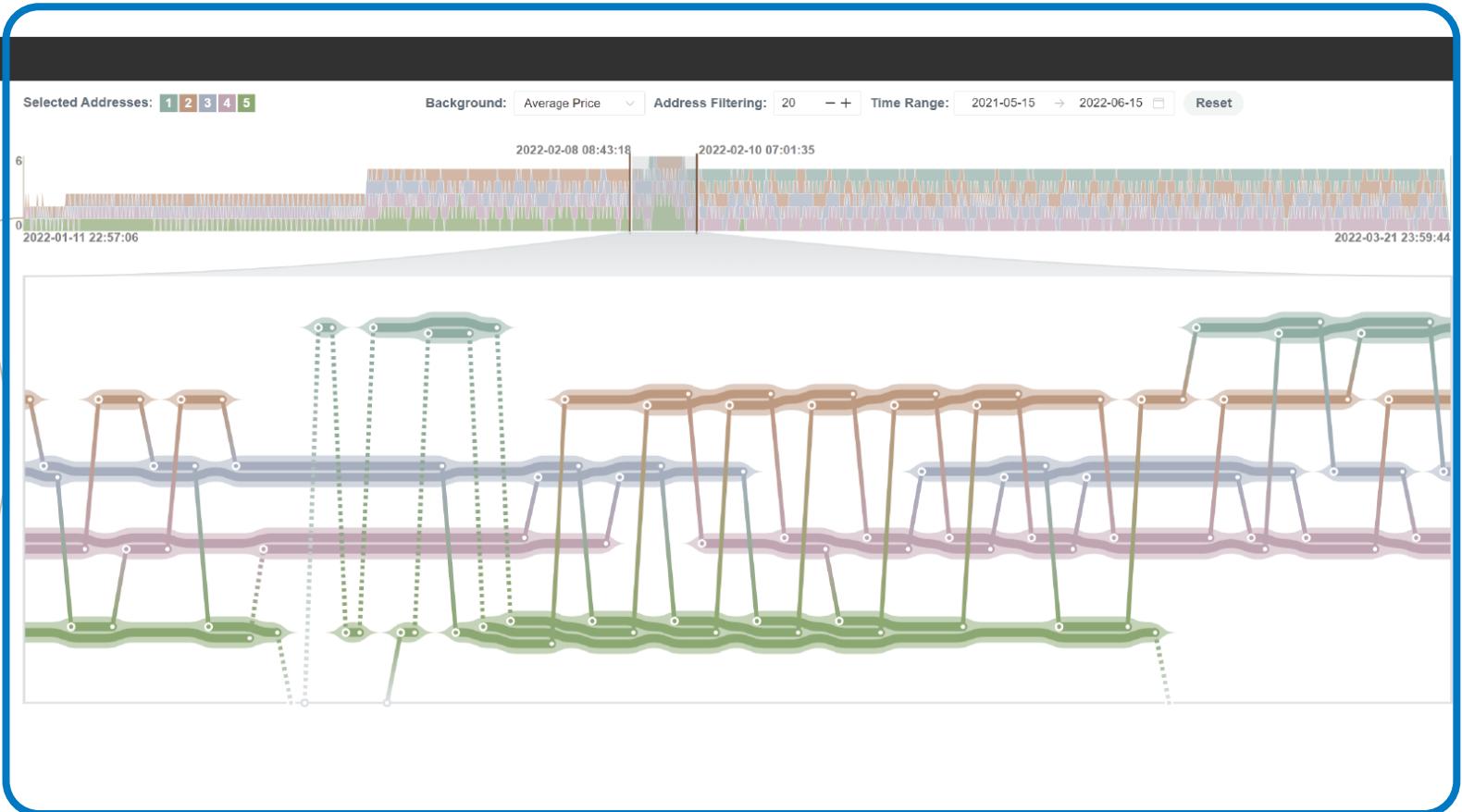
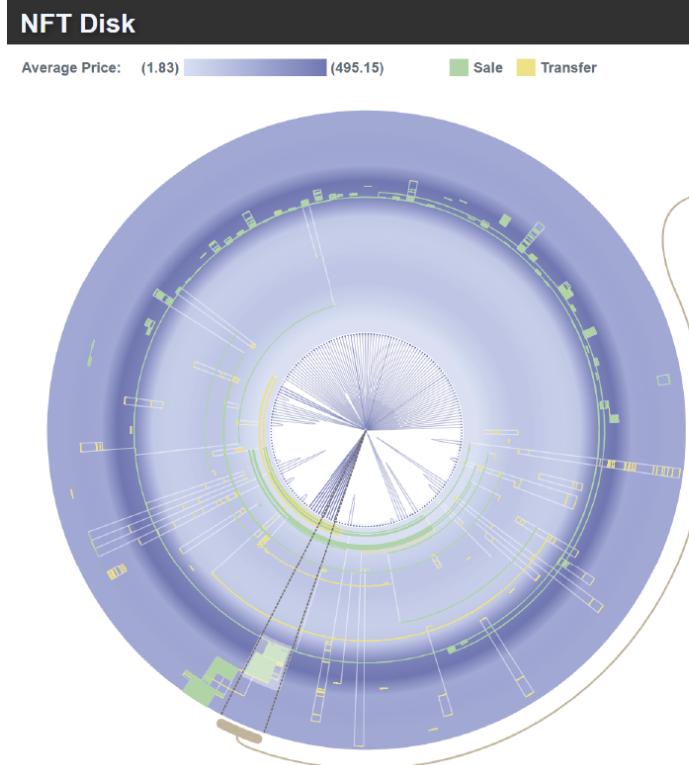
Flow Module



Disk Module

Overview Transactions

Suspicious addresses

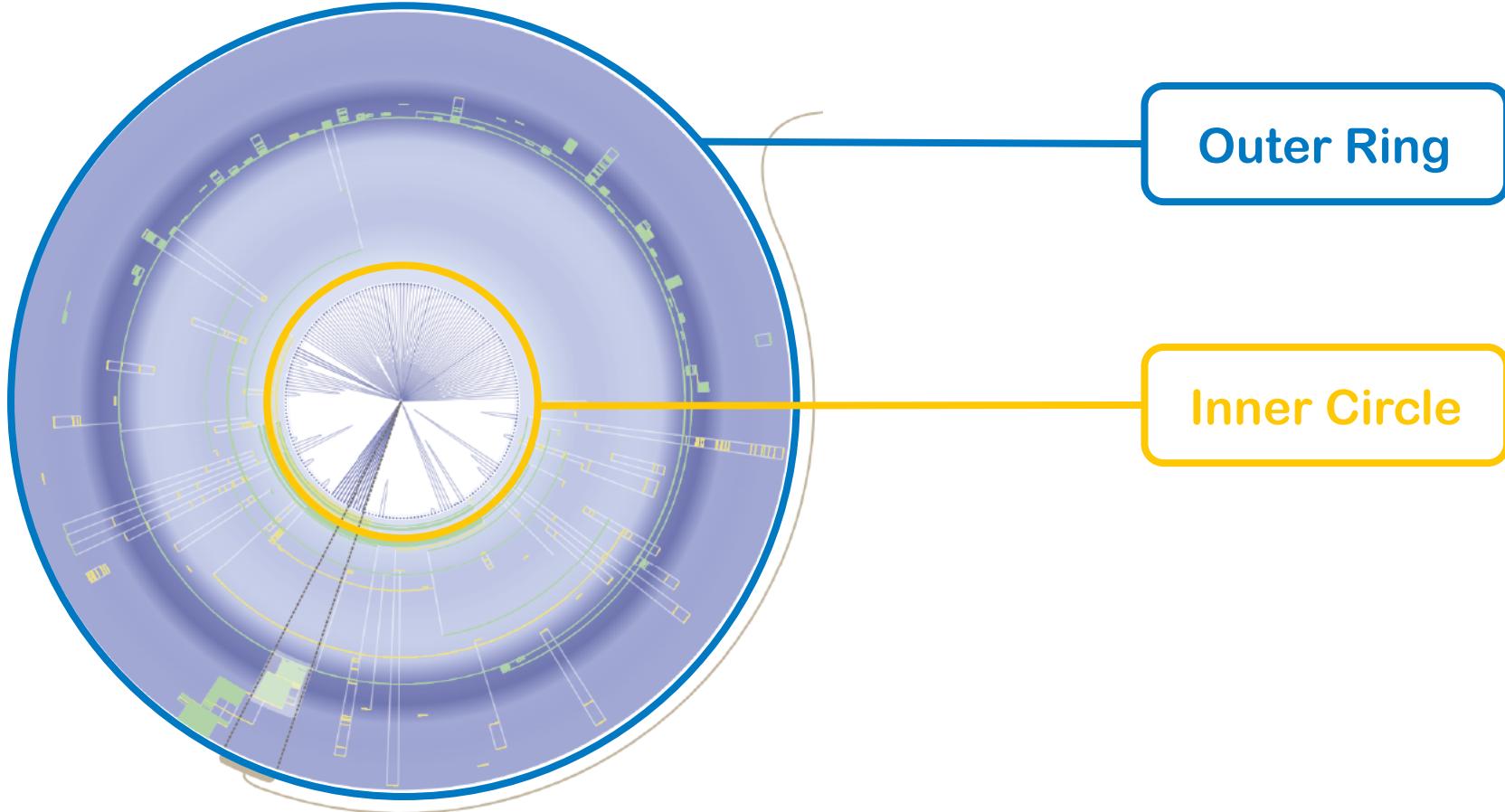


Show NFT flows among suspicious addresses at multiple levels.

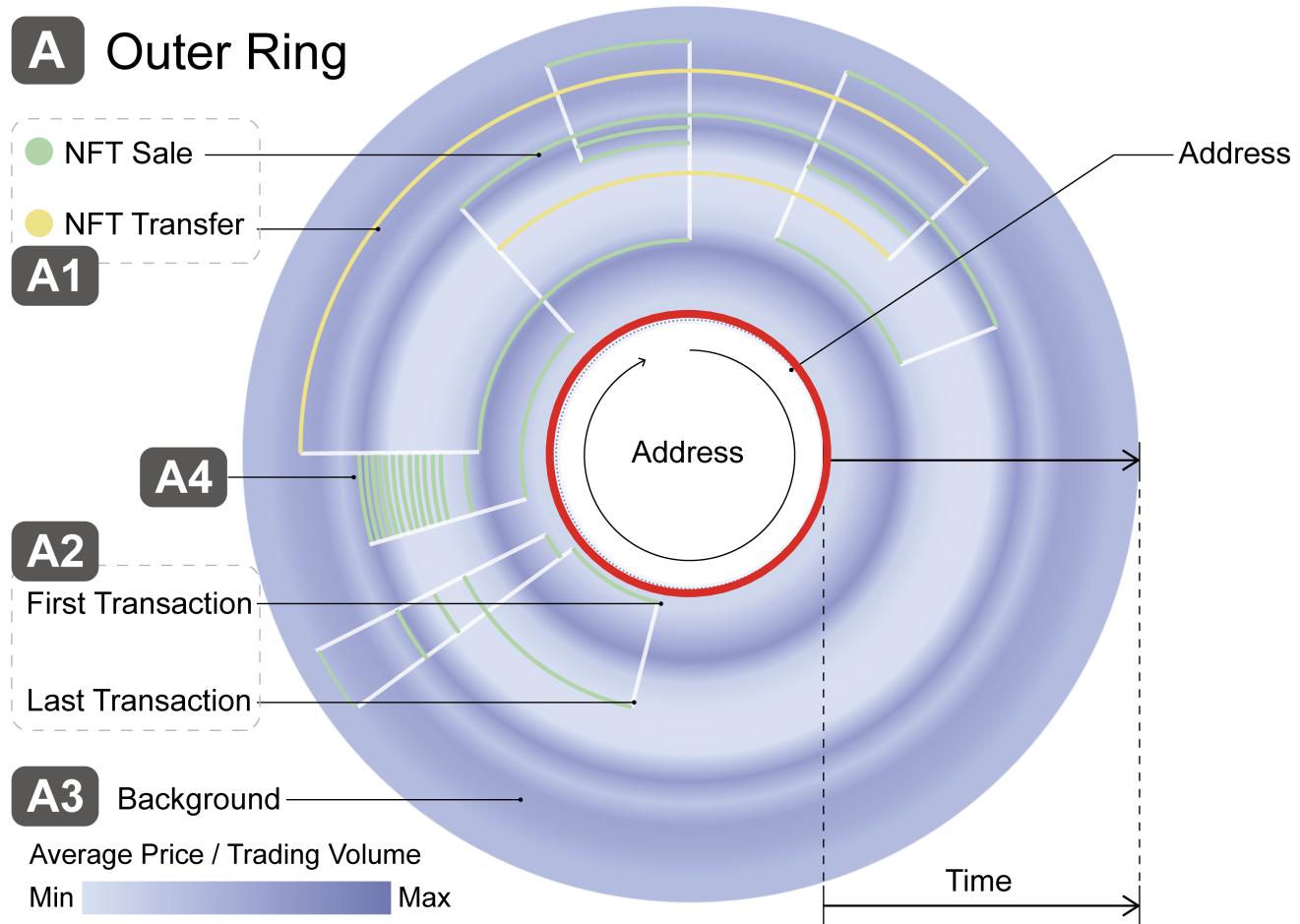
Flow Module

Disk Module

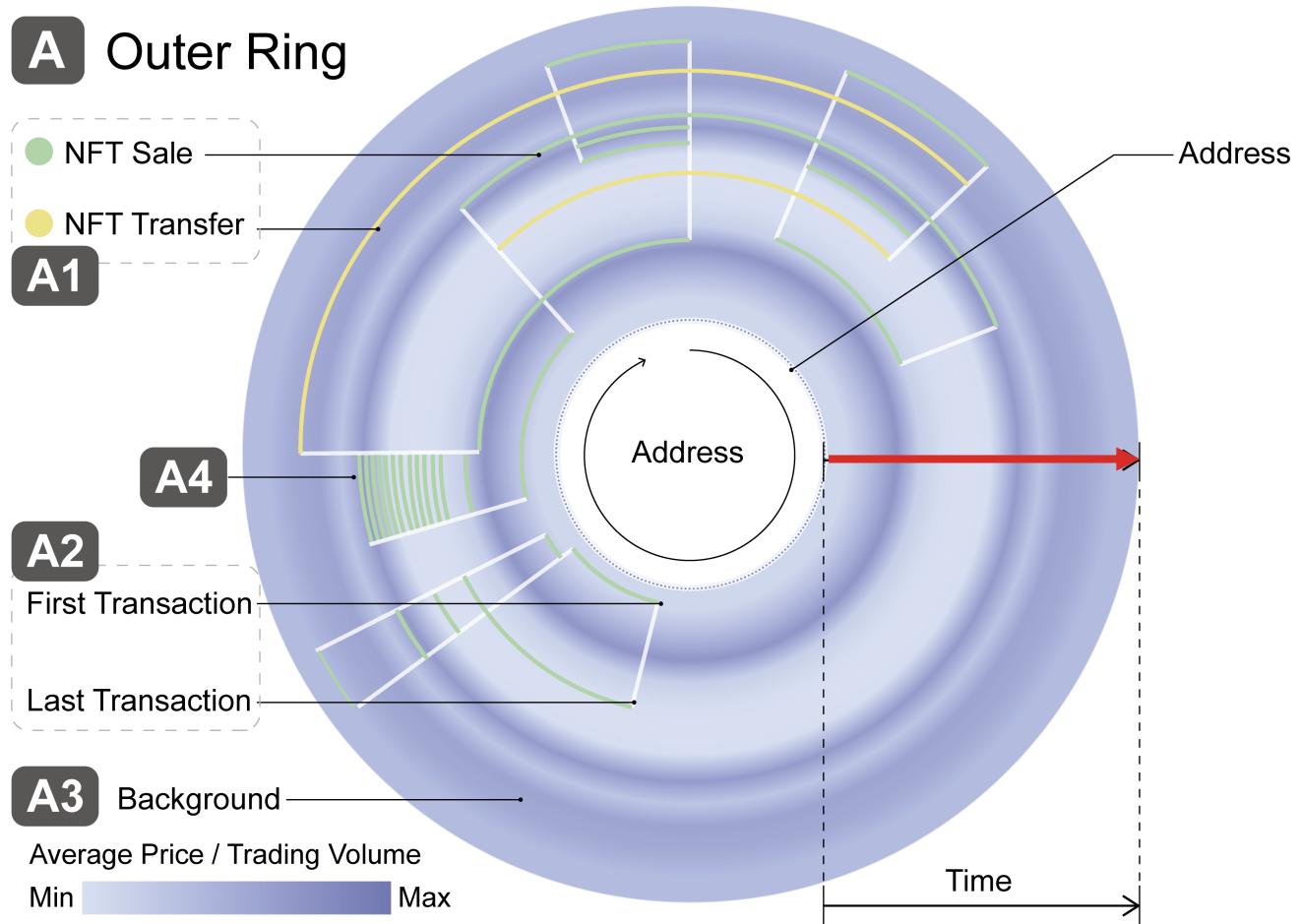
Average Price: (1.83) (495.15) Sale Transfer



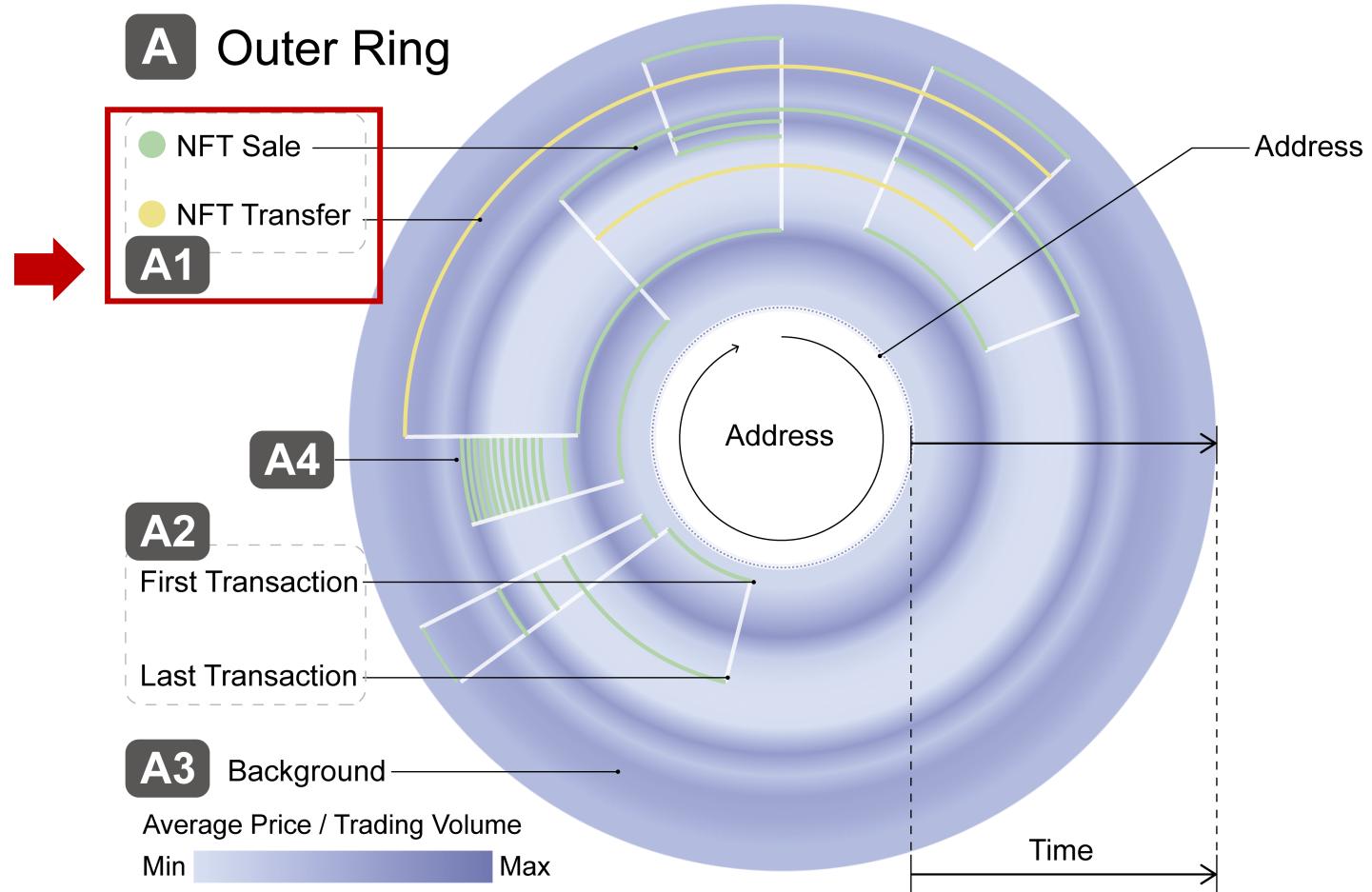
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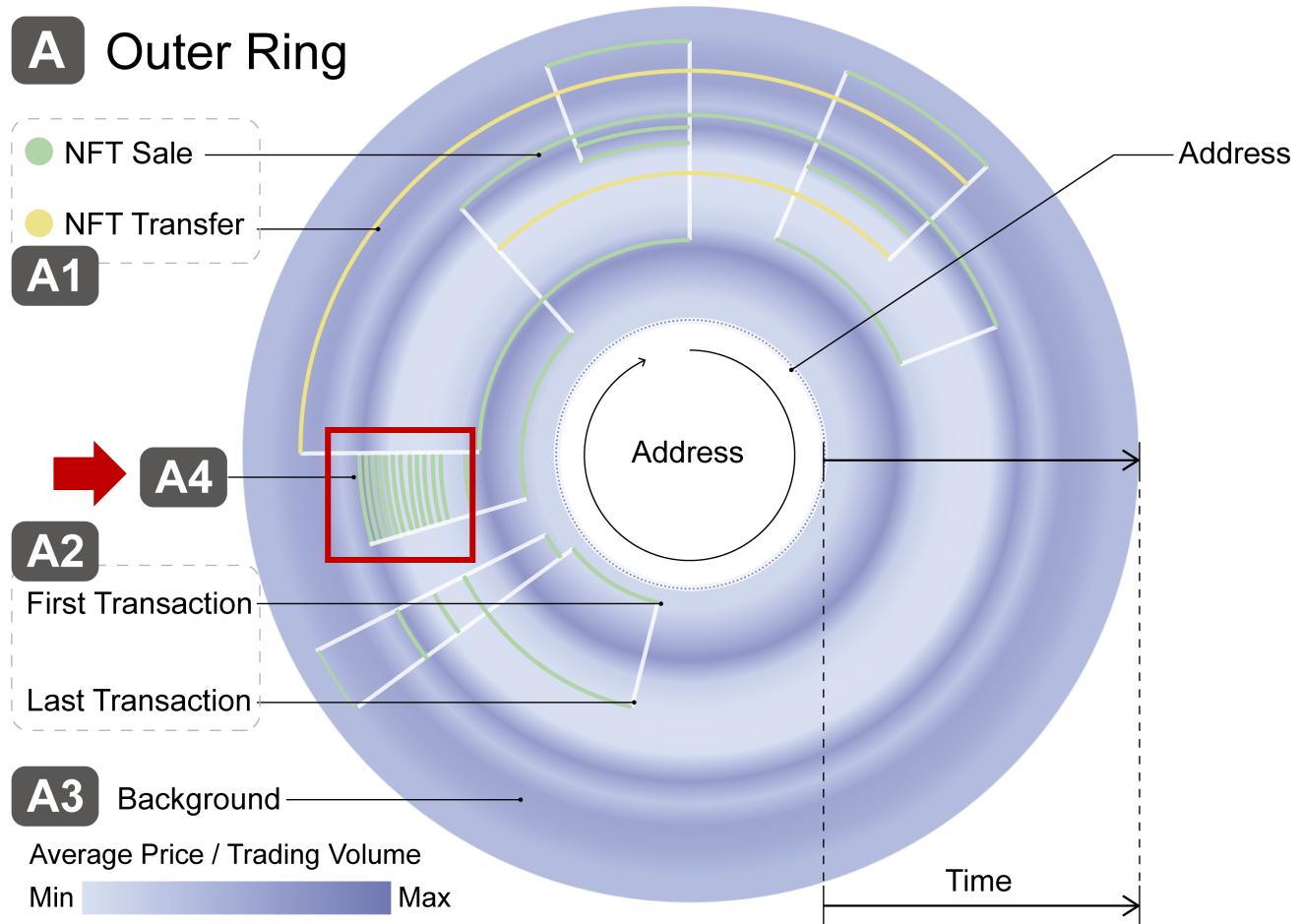
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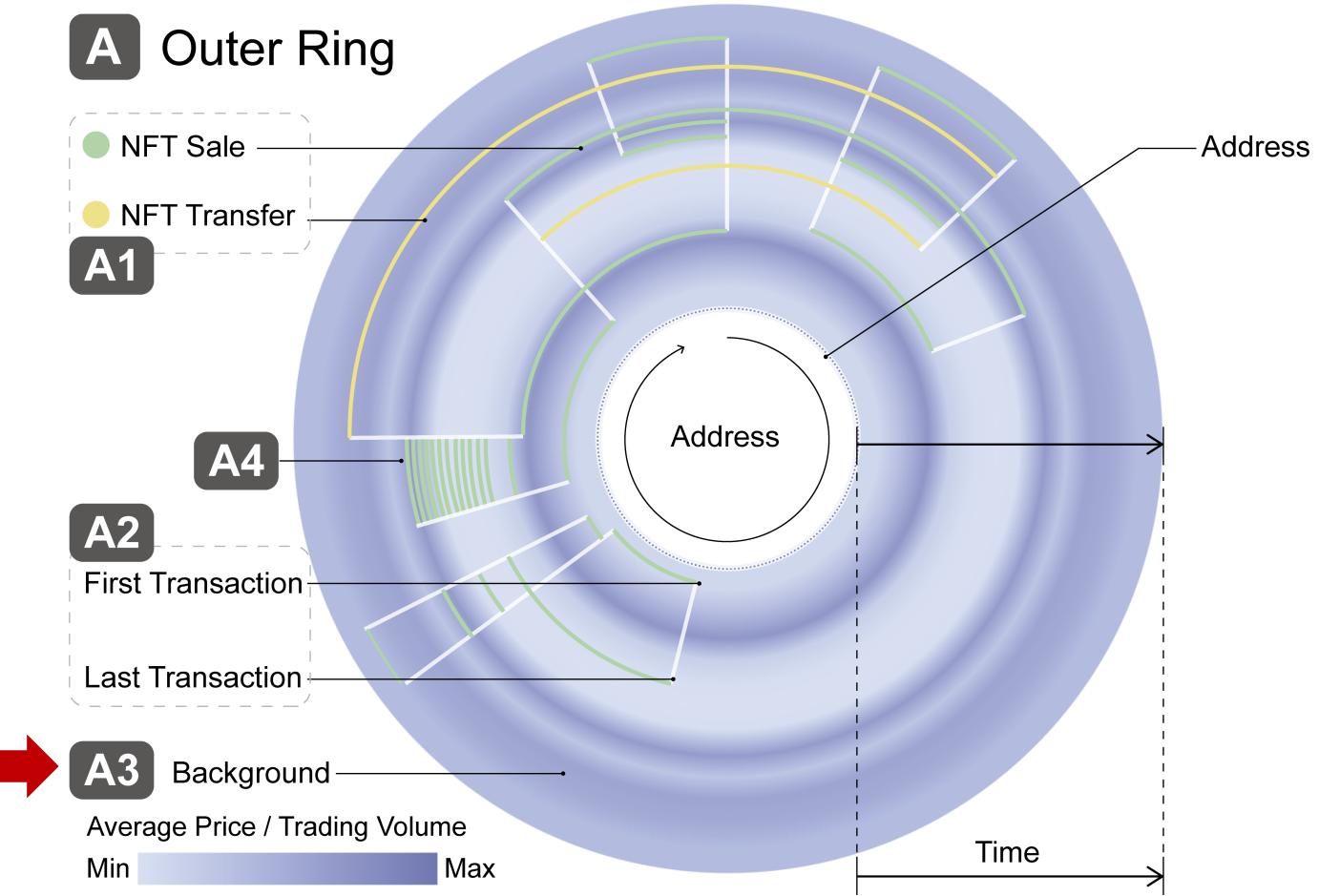
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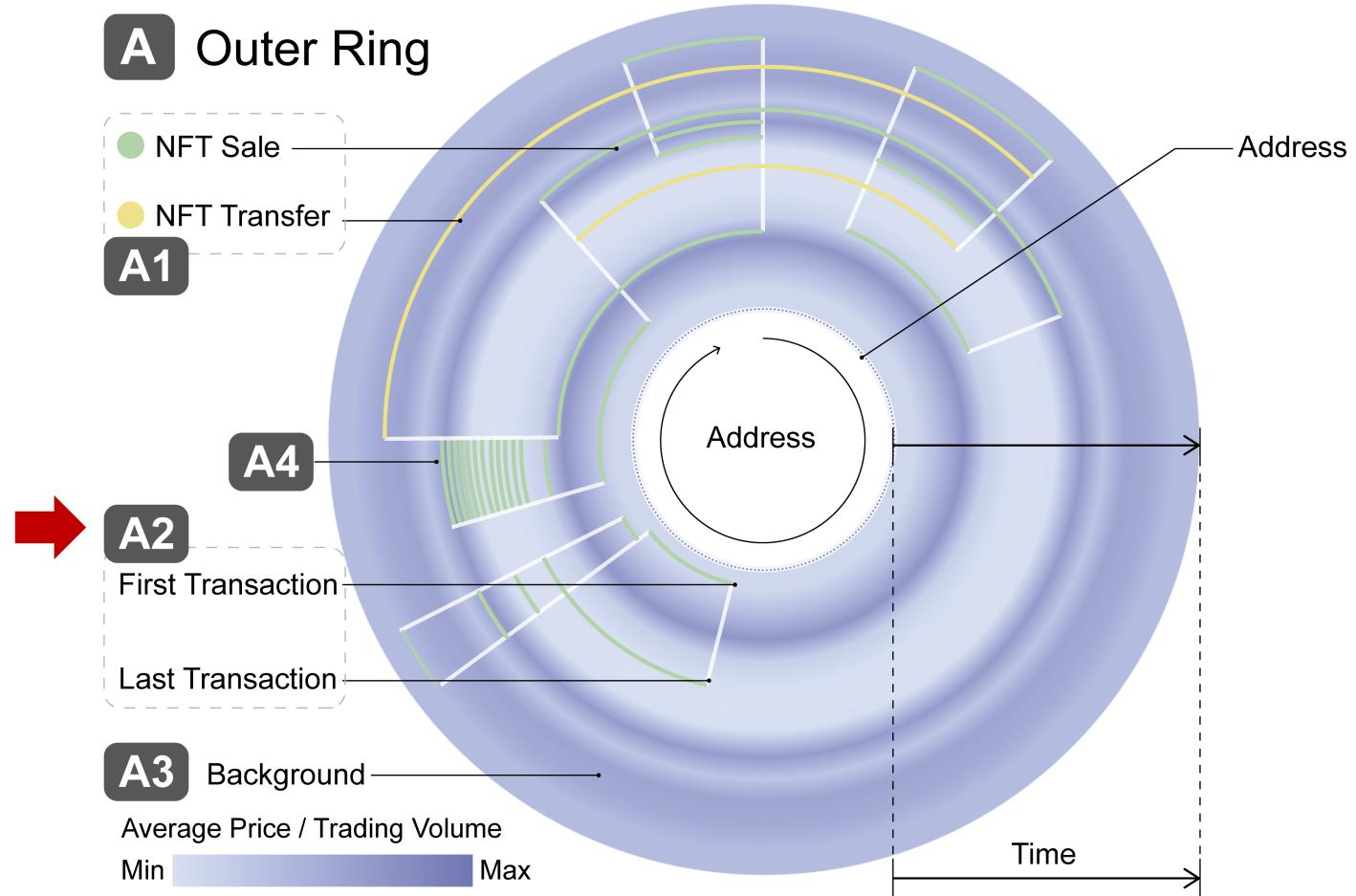
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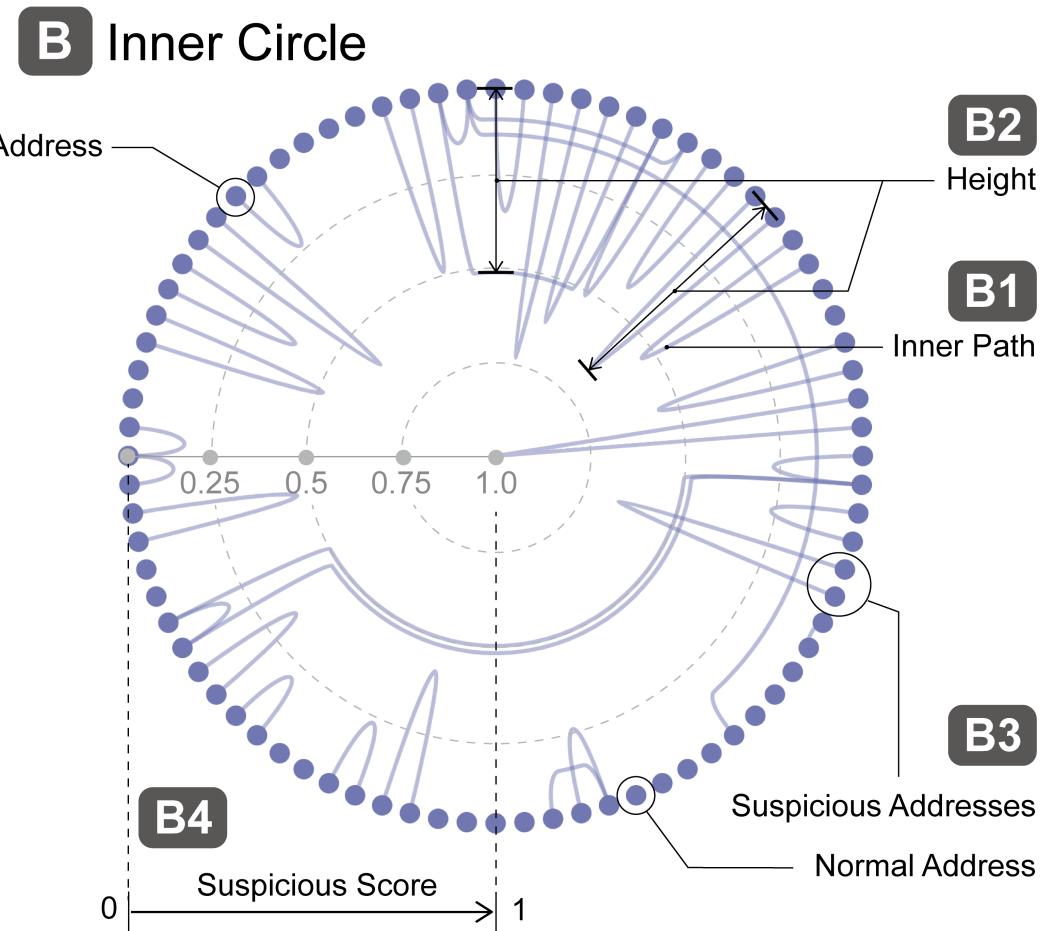
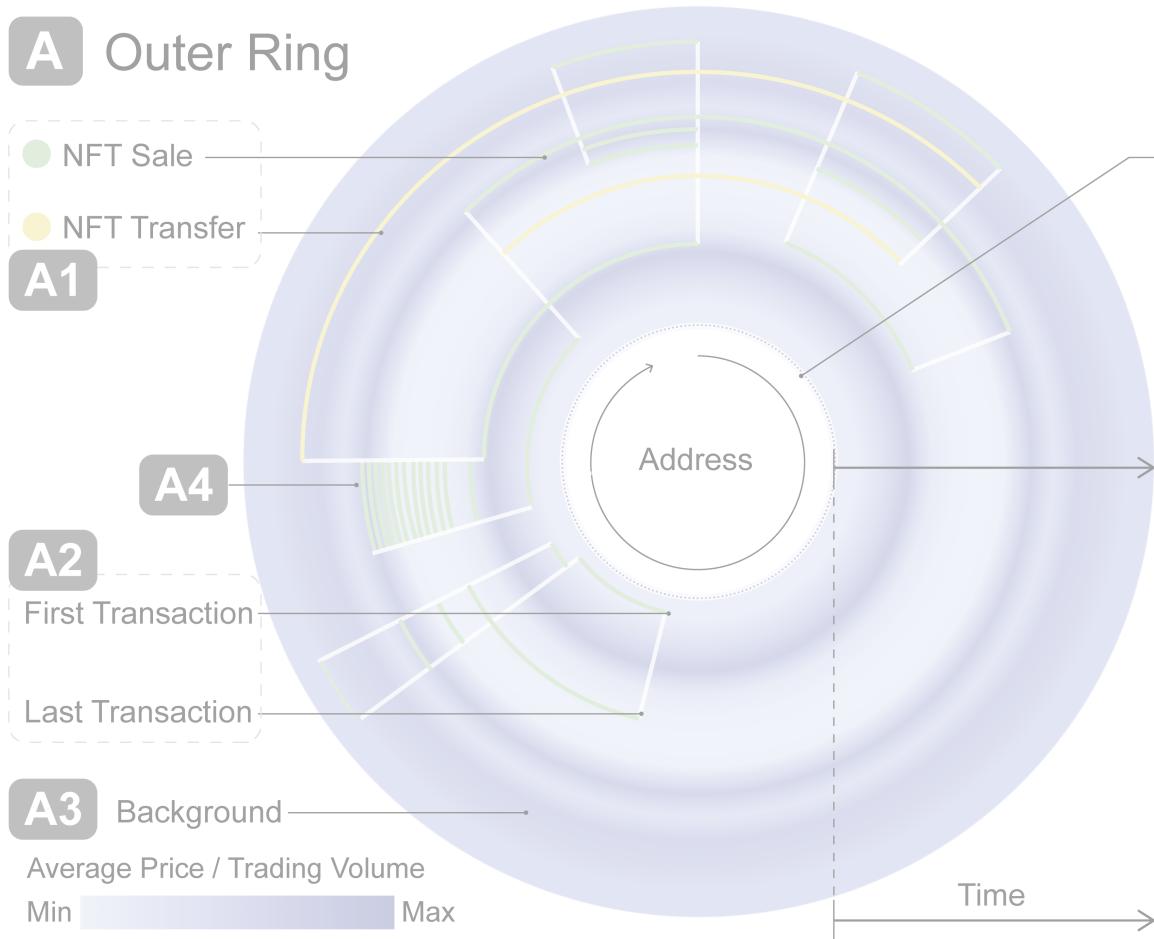
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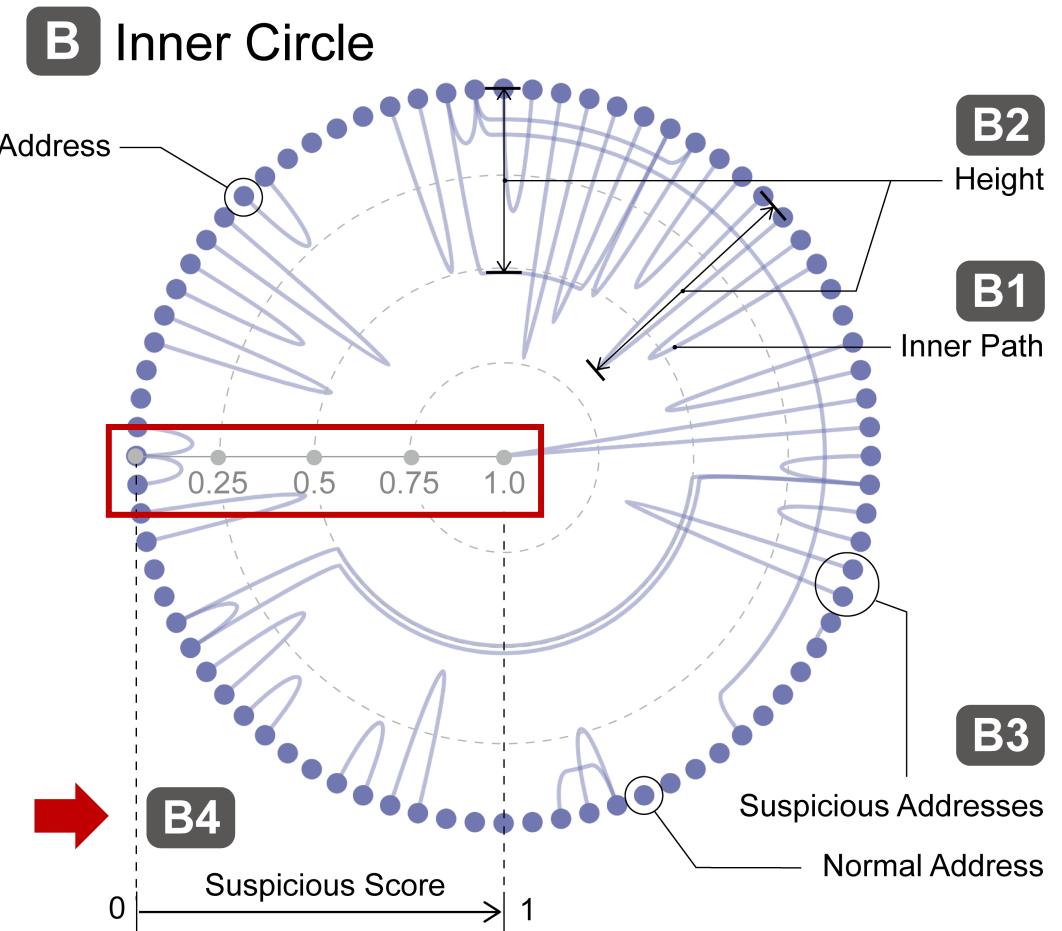
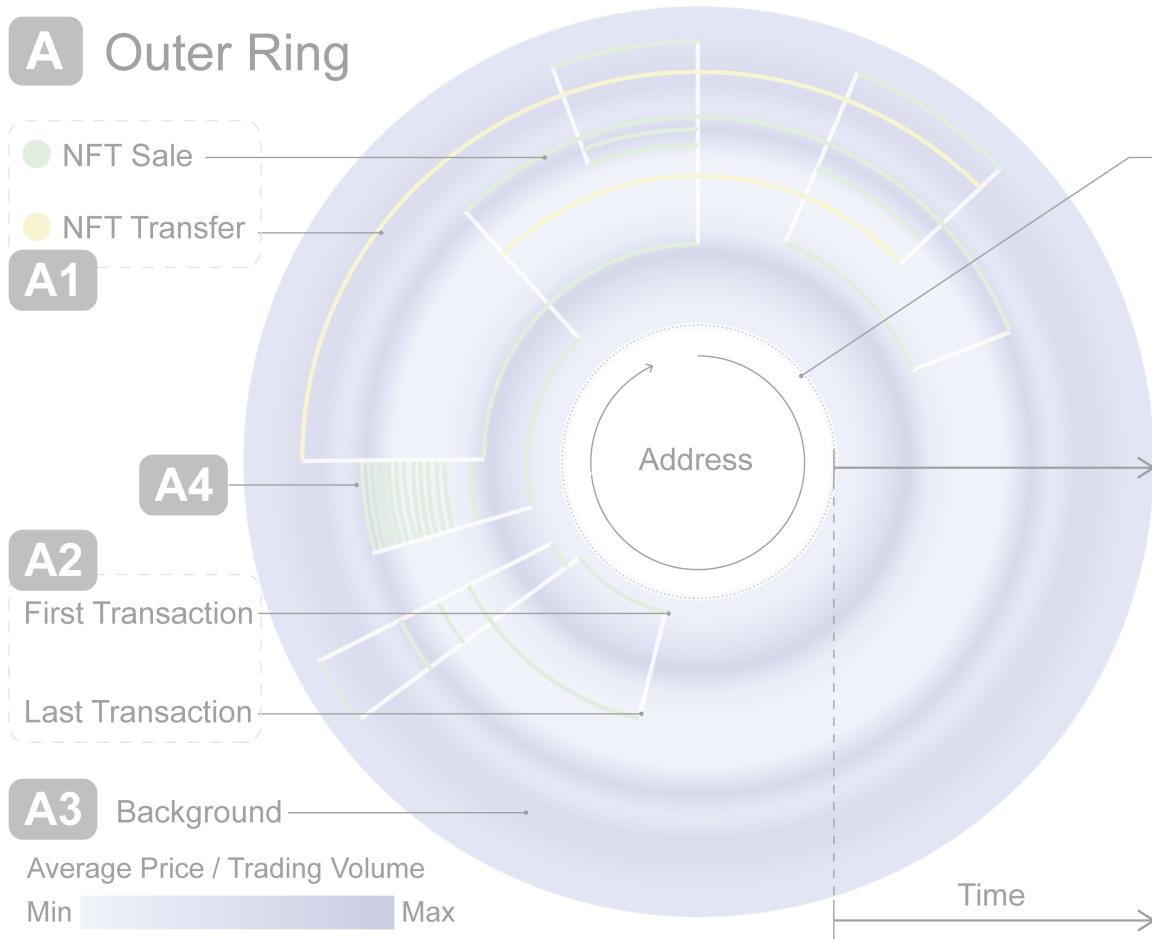
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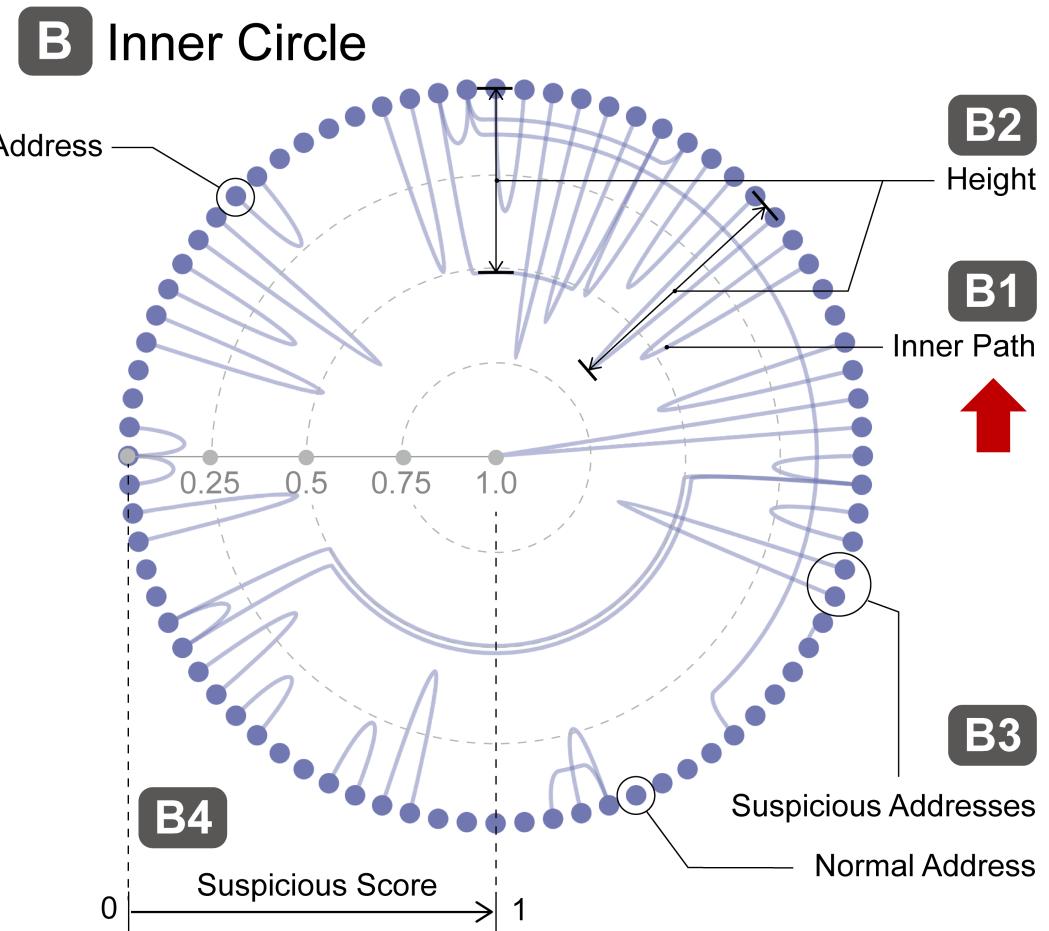
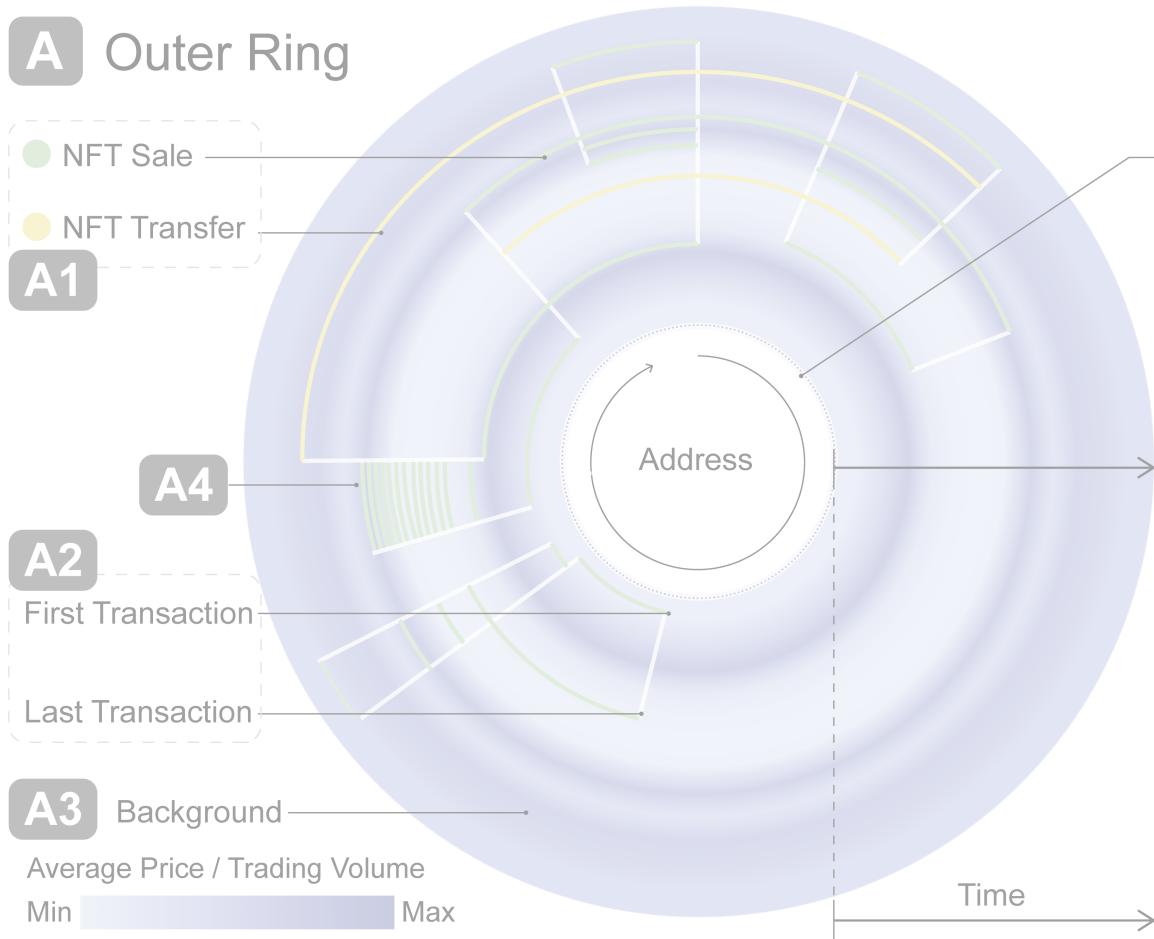
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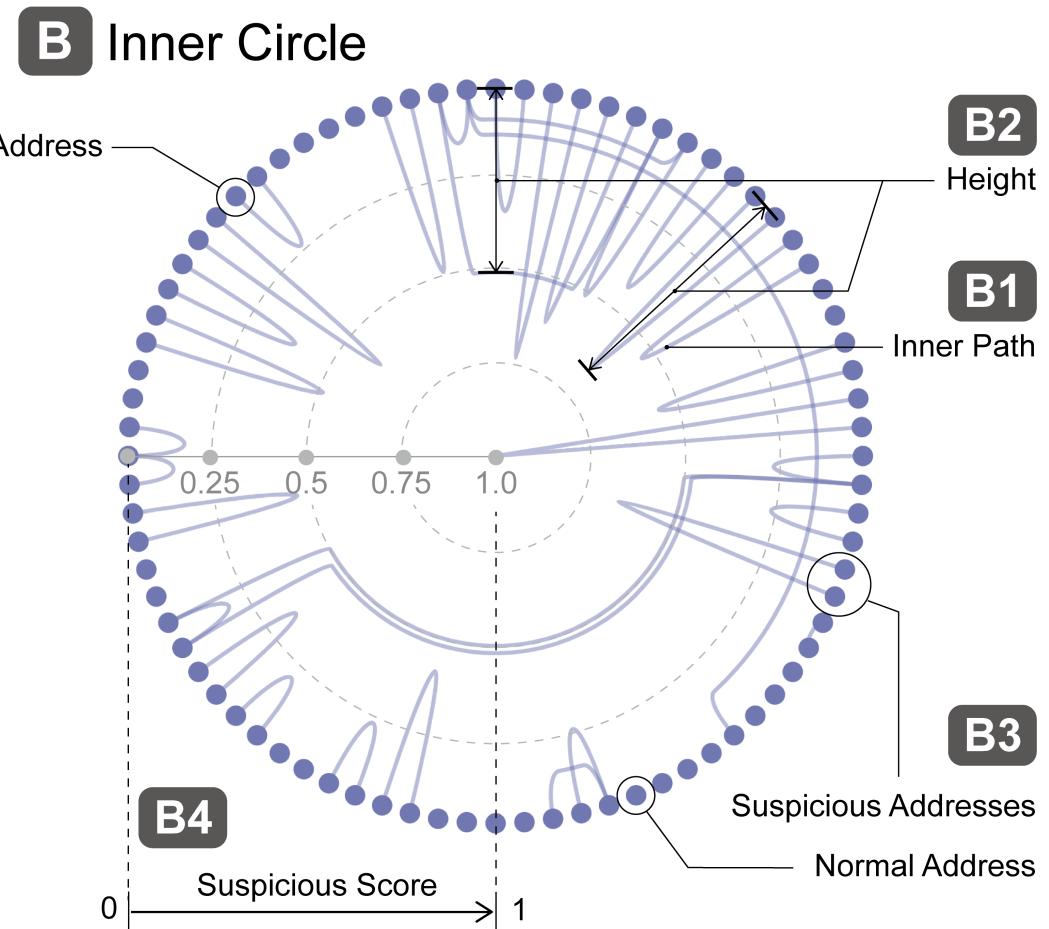
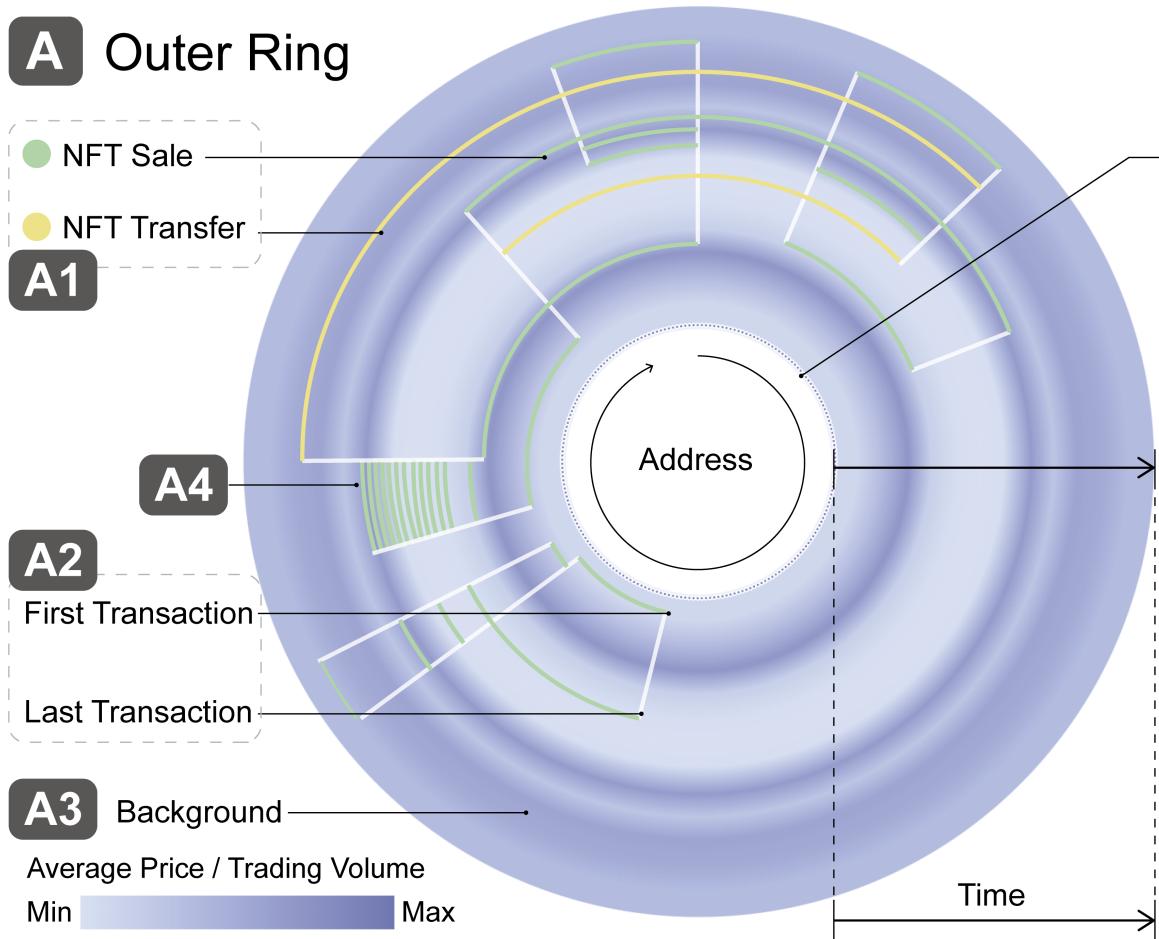
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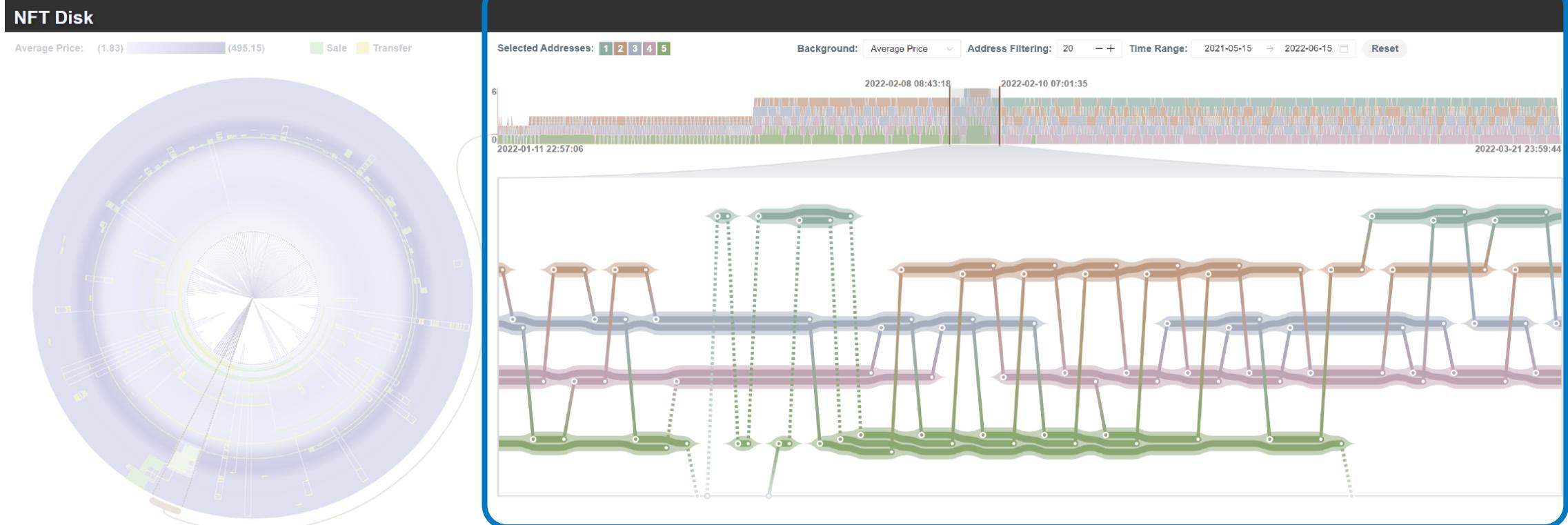
Disk Module



Disk Module

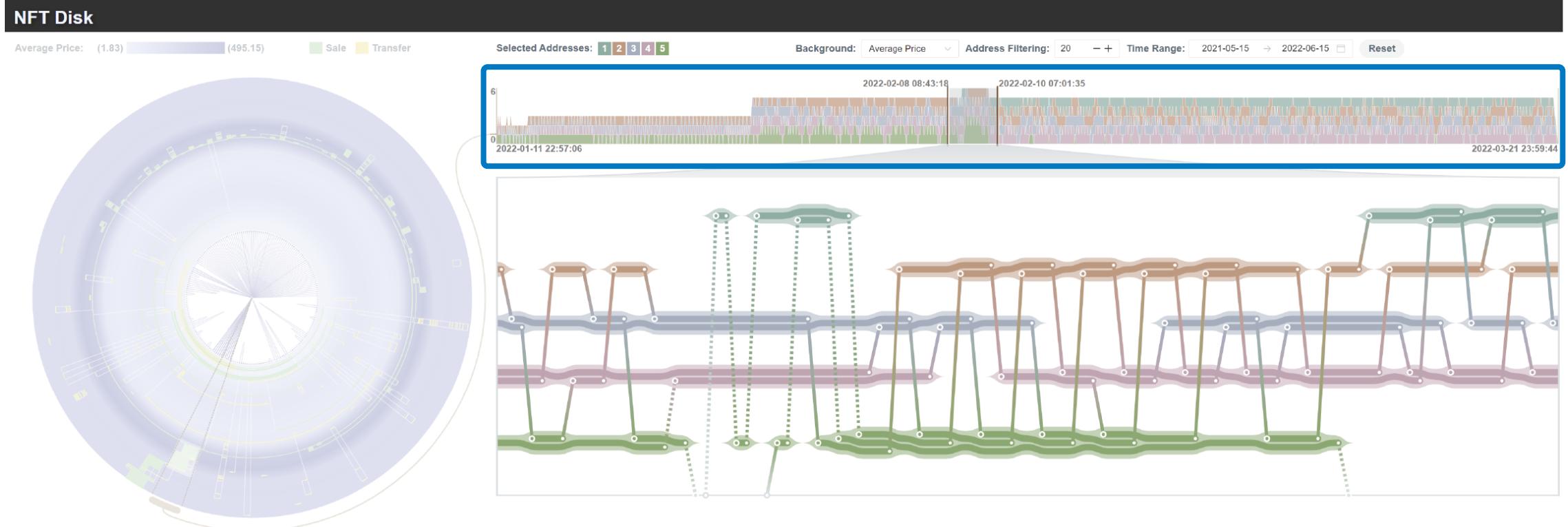


Flow Module

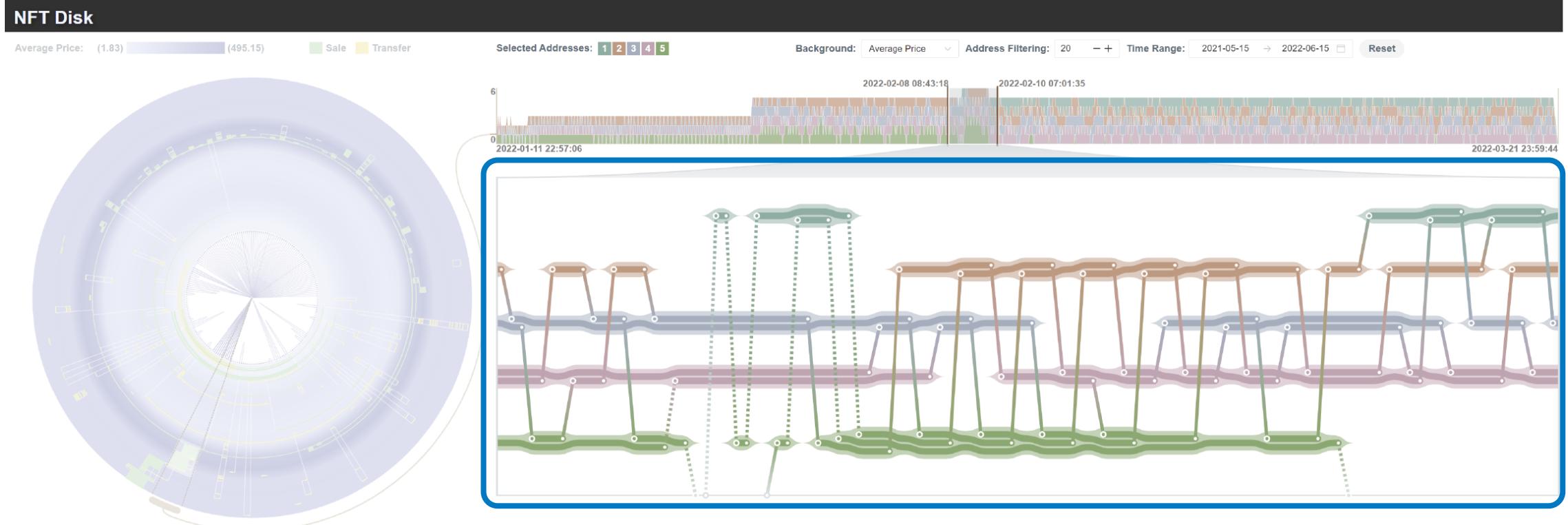


Flow Module

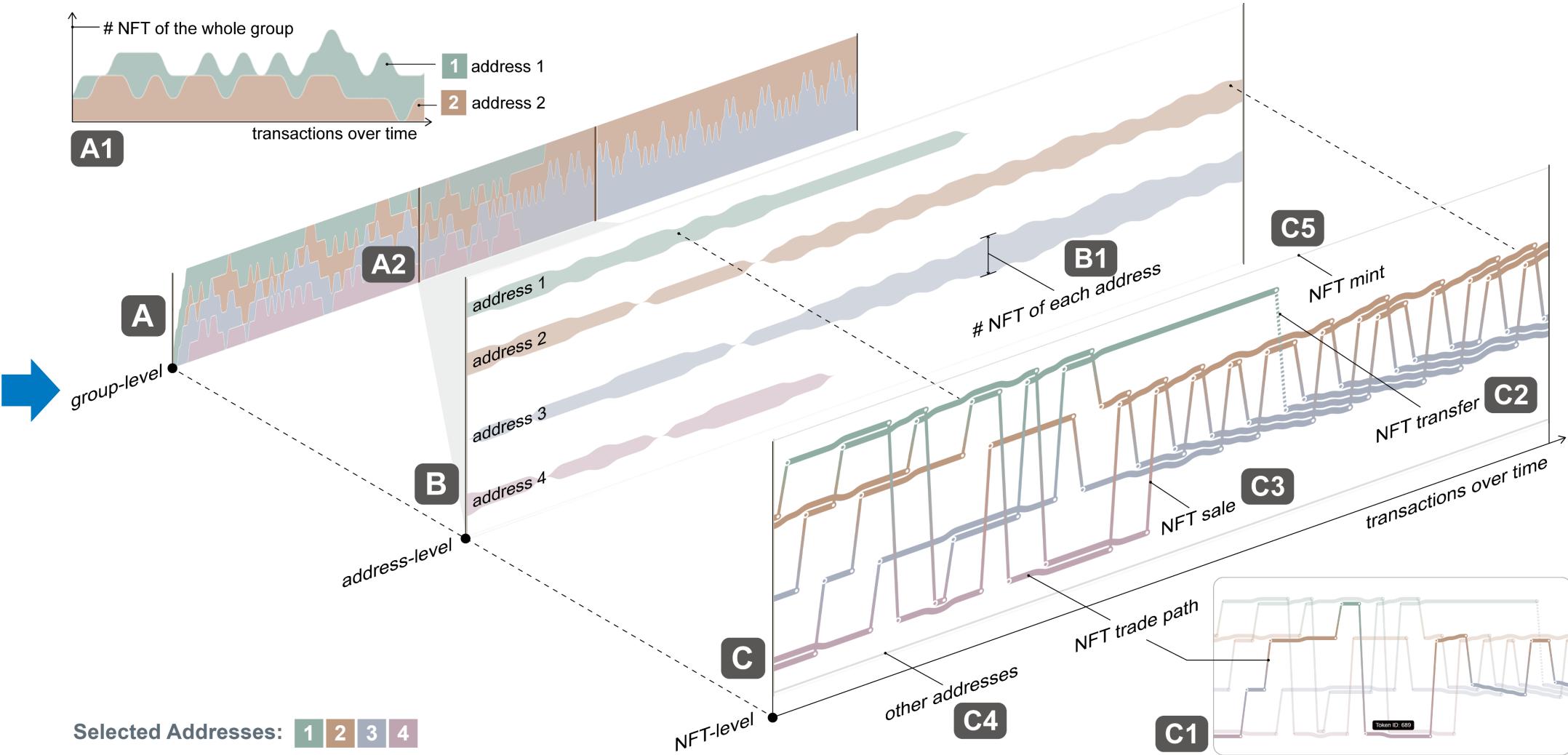
Flow Module



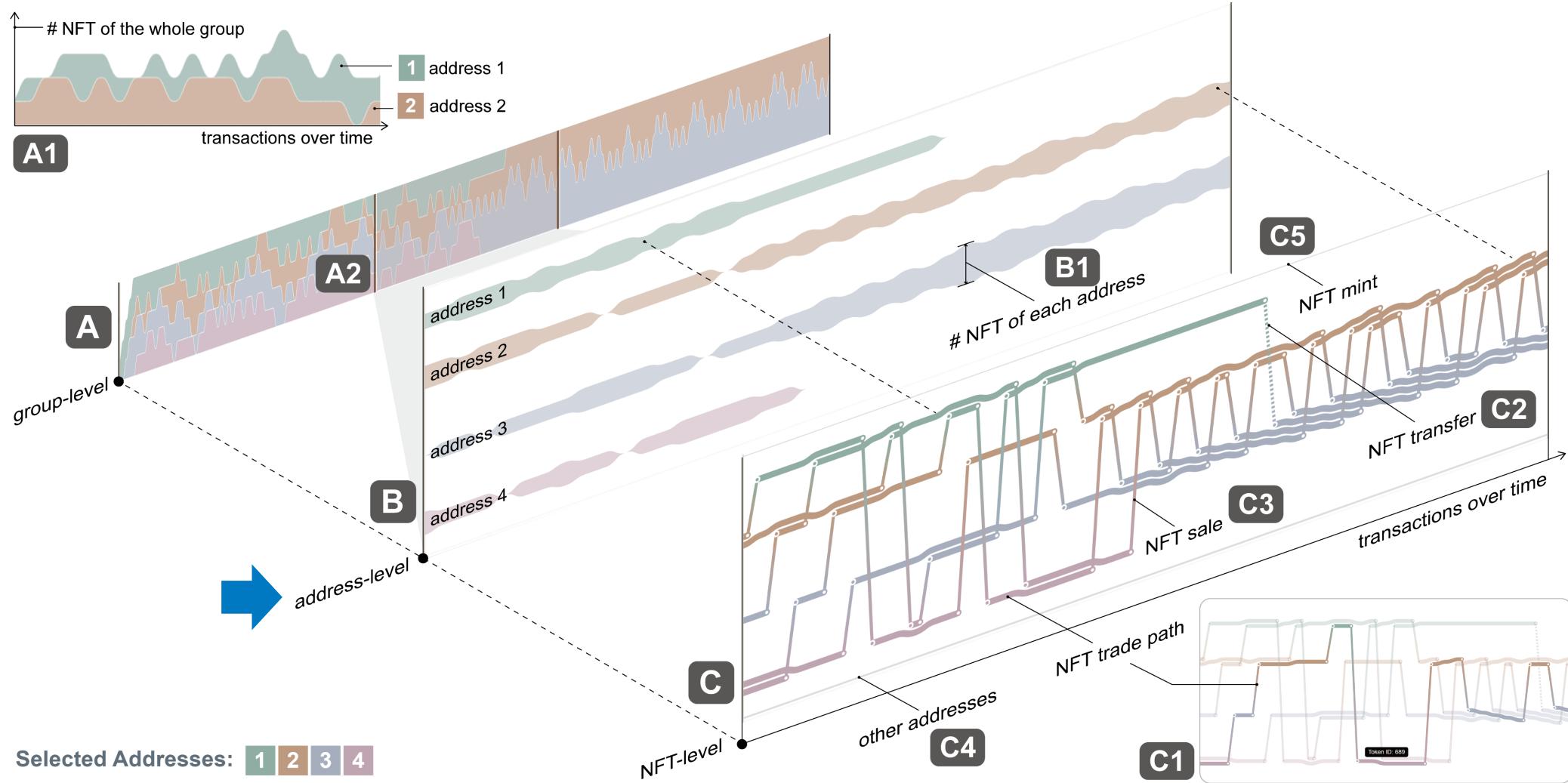
Flow Module



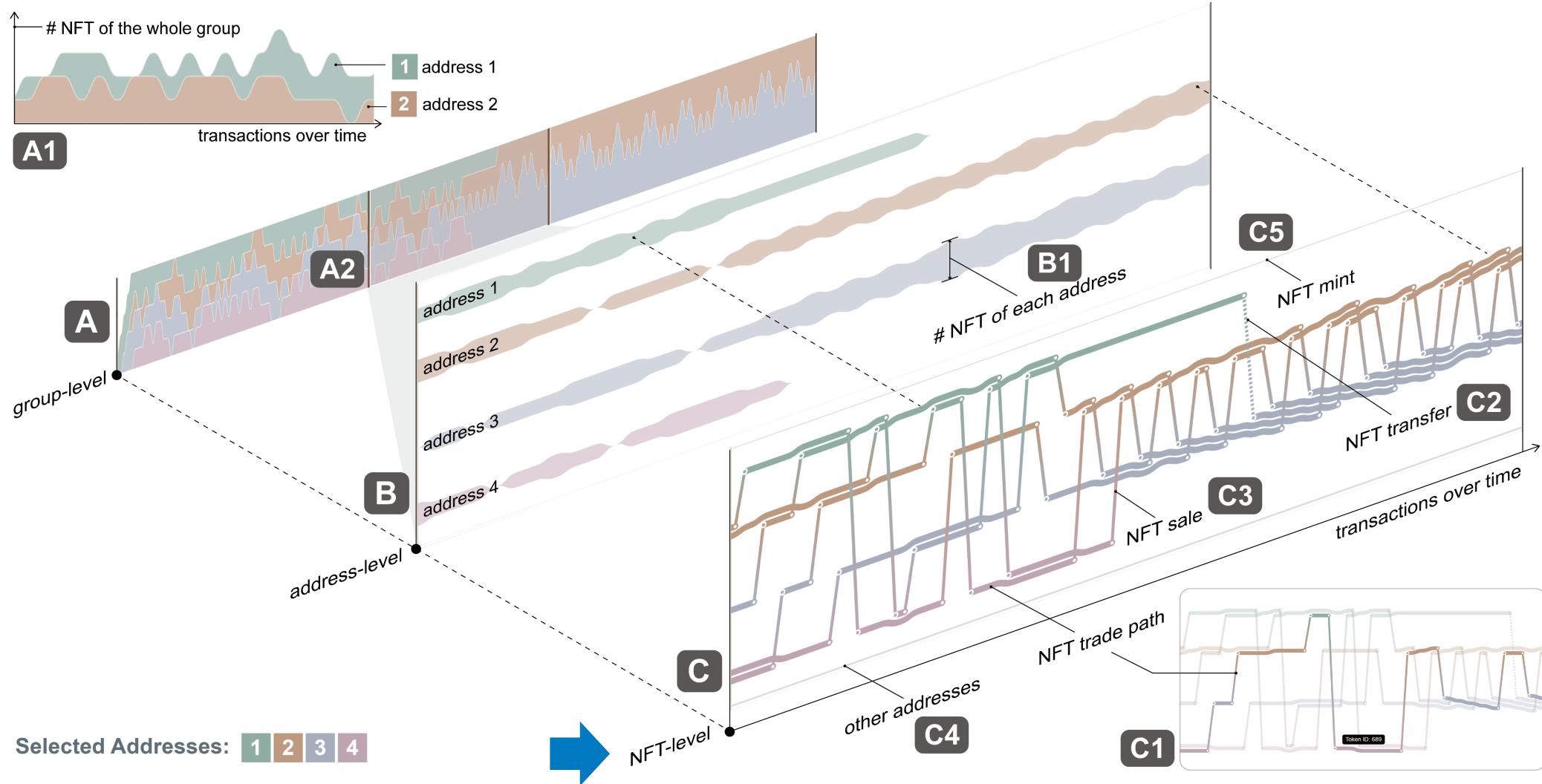
Flow Module



Flow Module



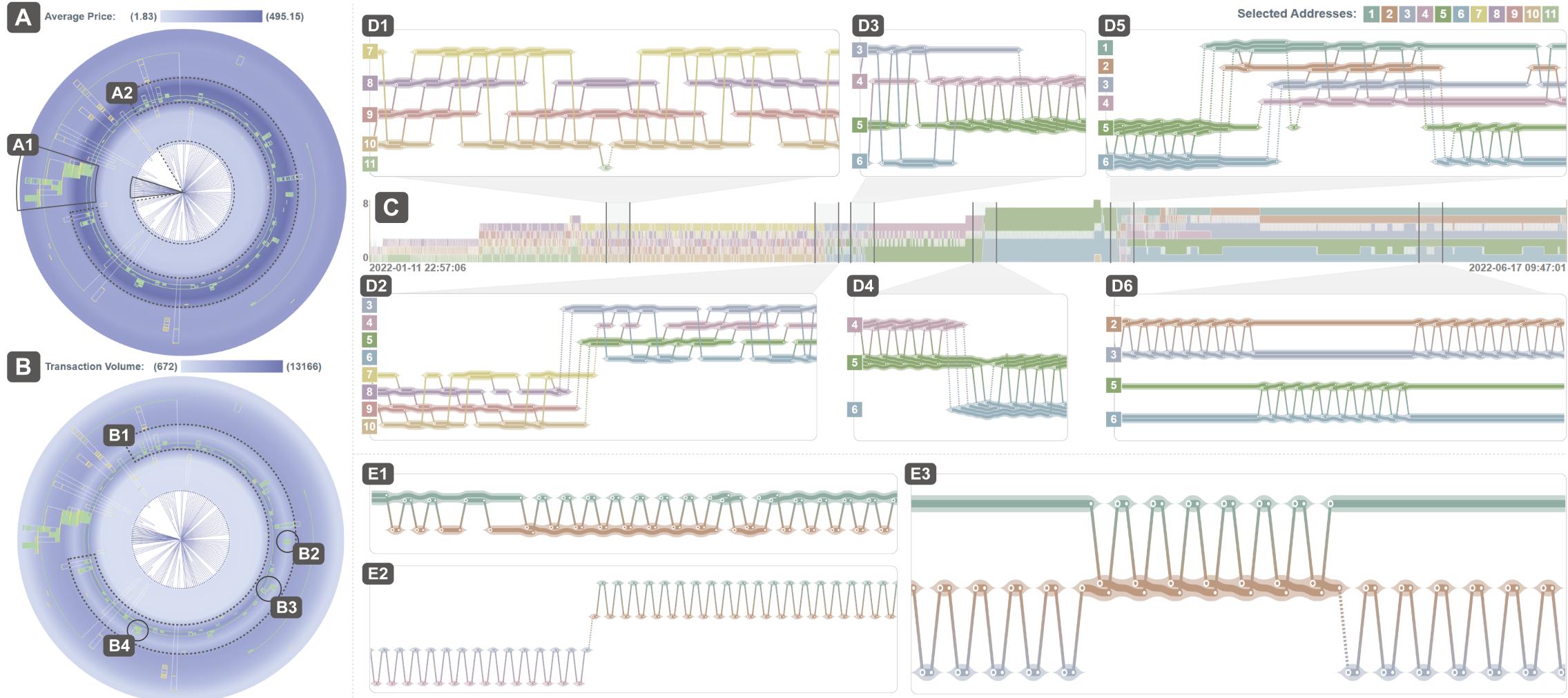
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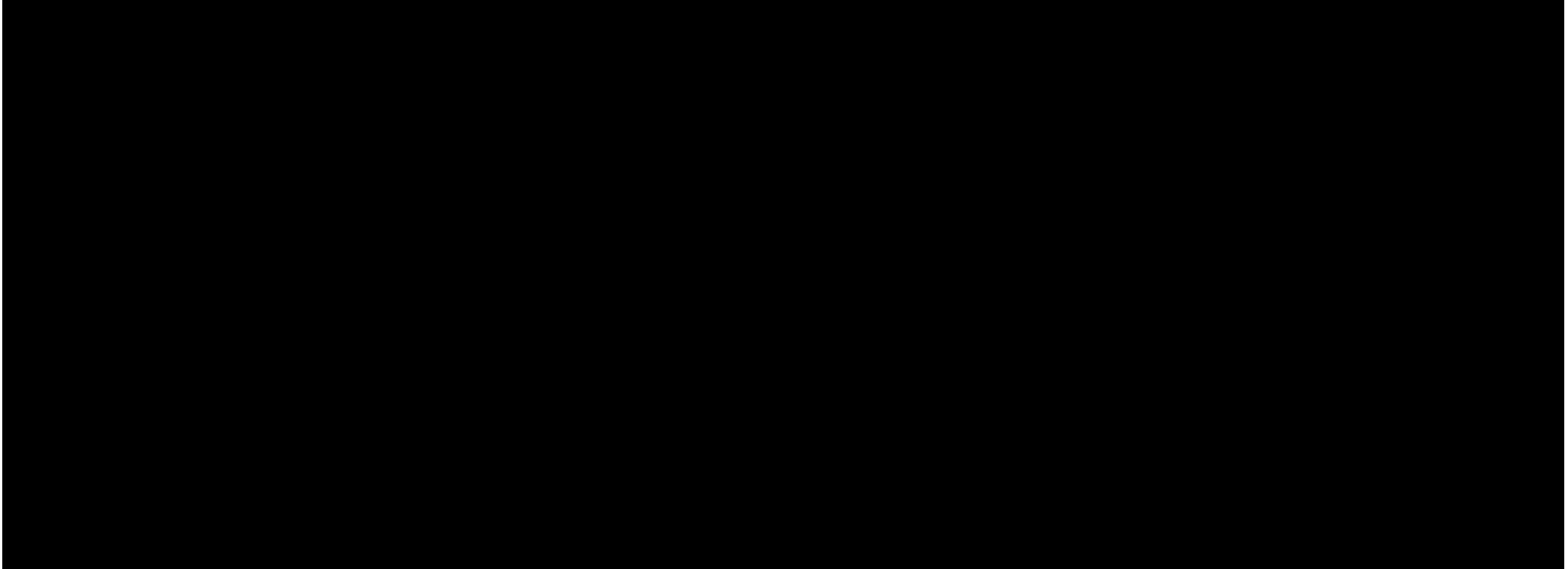
Evaluation

- Two case studies
- User interview with 14 real NFT investors

Case Study



Case Study

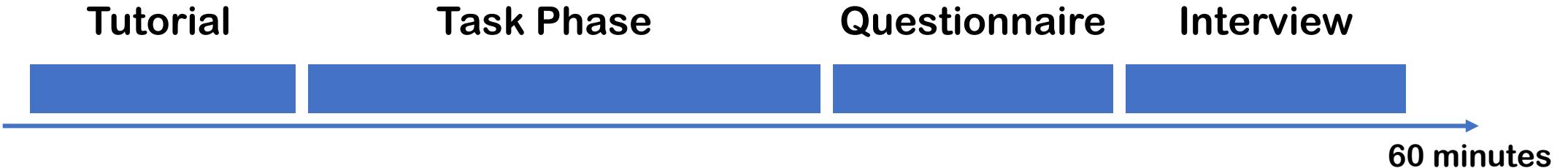


User Interview

Online study with **14** NFT investors (4 females, 10 males, age_{mean} = 28)

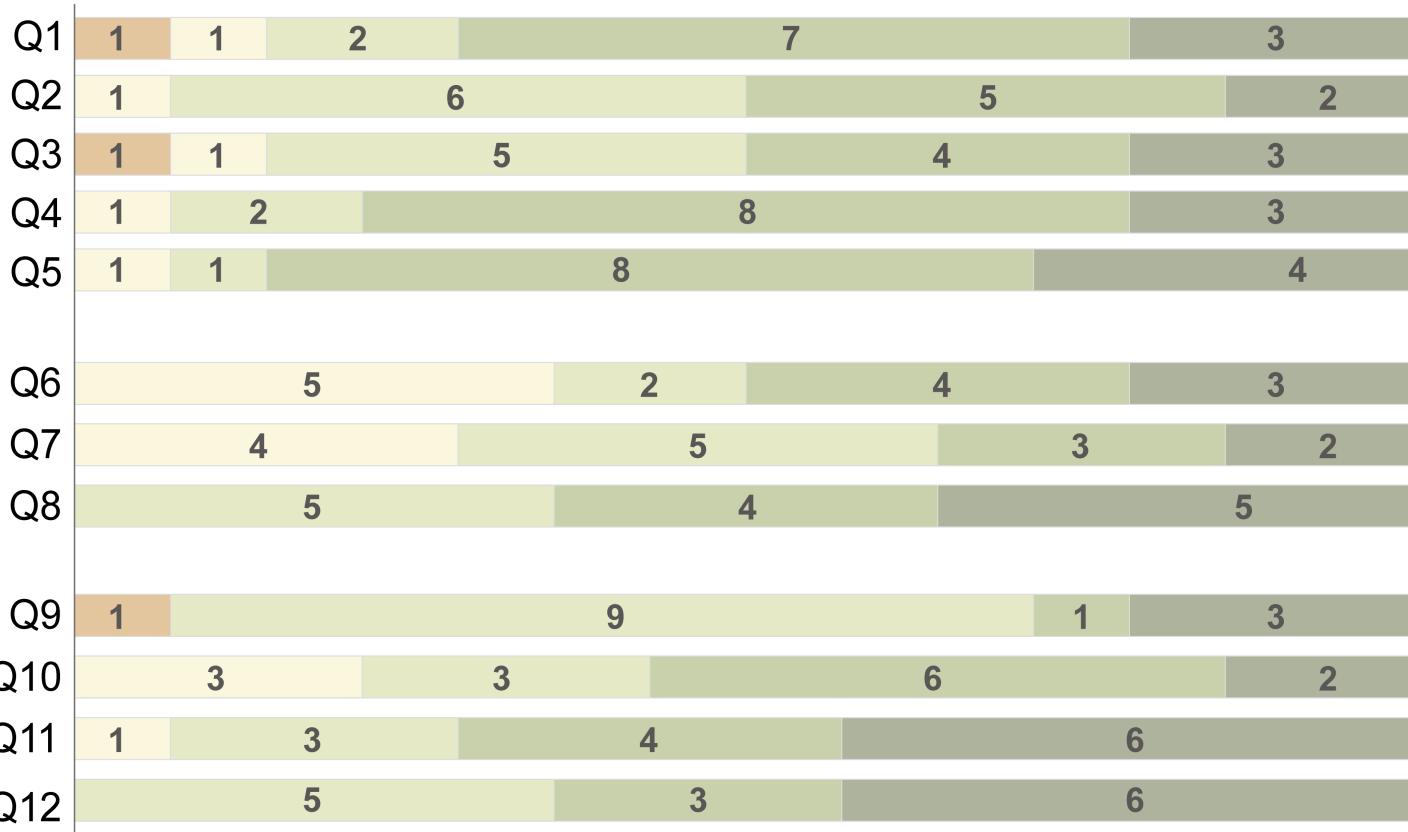
Task:

- T1. Initialize the visualization by using interactions components to filter out undesired information.
- T2. Observe the Disk Module to find suspicious addresses and time periods and brush to select them.
- T3. Analyze the NFT flows at the group level by the stacked area chart of the Flow Module.
- T4. Brush a period in the stacked area chart and check the detailed NFT flows in the flow-based chart.



User Interview

Workflow Effectiveness



Strongly Disagree 1: 2: 3: 4: 5: 6: 7: Strongly Agree

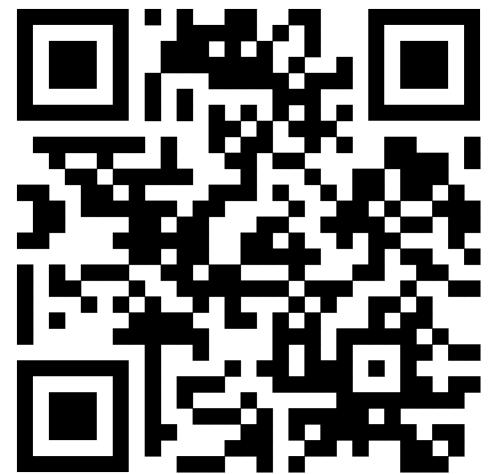
■ Summary

- Cooperated with NFT investors to collect design requirements;
- Proposed NFTDisk to help investors detect and analyze wash trading;
- Conducted case studies and user interview to evaluate NFTDisk;



NFTDisk: Visual Detection of Wash Trading in NFT Markets

Paper Link



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Late-Breaking Work



Code Will Tell: Visual Identification of Ponzi Schemes on Ethereum

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2. Singapore Management University

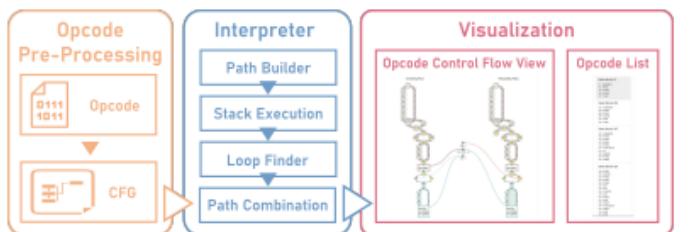
Motivation

- Due to the decentralization and anonymity of Ethereum, Ponzi schemes have been easily deployed and caused significant losses to investors.
- However, there are still no explainable and effective methods to help investors easily identify Ponzi schemes and validate whether a smart contract is actually a Ponzi scheme.
- We propose *PonziLens*, a novel visualization approach to help investors achieve early identification of Ponzi Schemes by investigating the operation codes of smart contracts.

Features of Ponzi Schemes

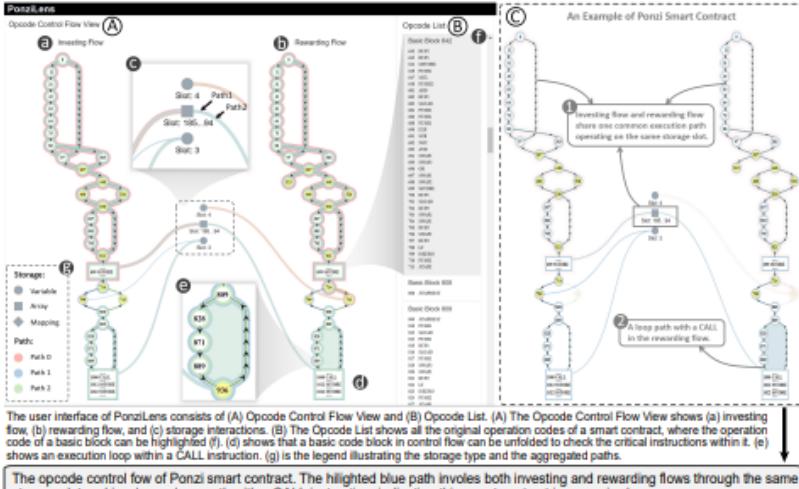
- ① Investing flow and rewarding flow share one common execution path operating on the same storage slot.
- ② A loop during rewarding for cases where ether is returned to more than one past investor.

Pipeline of PonziLens

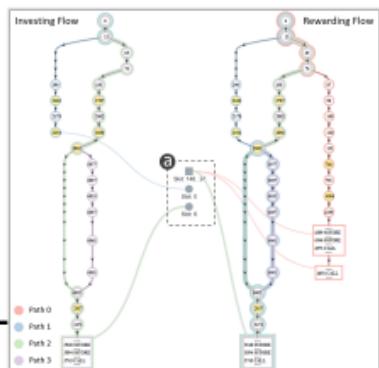


The opcode control flow of EthPledge, a smart contract for charity. PonziLens shows the investing flow and the rewarding flow, as well as their interactions with storage slots (a). The execution paths involved in the investing and rewarding flows use different storage slots, indicating that investments cannot be transferred to prior investors, so this smart contract is NOT a Ponzi scheme.

PonziLens: A visualization tool to achieve early detection of Ponzi Schemes on Ethereum



An Example of Non-Ponzi Smart Contract



LBW-B044

Code Will Tell: Visual Identification of Ponzi Schemes on Ethereum



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Design Requirements

- R1 Analyze wash trading in the scope of NFT collection;
- R2 Recognize suspicious transactions and addresses from the overview;
- R3 Reveal wash trading features at multiple levels;
- R4 Display the detailed transaction patterns of wash trading;
- R5 Enable the evaluation of wash trading influence.

Participants

ID	Gender	Age	NFT Experience	Description
U1	Male	23	13 months	A creator of an NFT community and a key opinion leader on Twitter.
U2	Female	25	8 months	A product manager for multiple NFT projects.
U3	Male	30	12 months	An NFT investor who is good at using NFT analysis tools.
U4	Female	26	12 months	A creator of an NFT community and a key opinion leader on Twitter.
U5	Male	29	10 months	A creator of an NFT community and a leader of an NFT project.
U6	Male	25	12 months	A creator of an NFT community and a leader of three NFT projects.
U7	Female	23	7 months	An NFT investor engaged in the issuance of NFT projects.
U8	Male	27	10 months	An NFT investor engaged in the issuance of NFT projects.
U9	Male	27	6 months	An NFT investor who is good at using NFT analysis tools.
U10	Male	30	12 months	An NFT investor investing in cryptocurrencies for five years.
U11	Male	25	7 months	An NFT investor investing in cryptocurrencies for two years.
U12	Male	28	5 months	An NFT investor investing in cryptocurrencies for two years.
U13	Male	46	4 months	A professor whose research focus is digital economy.
U14	Female	28	5 months	A PhD student with two-year research experience in cryptocurrencies.

Implications

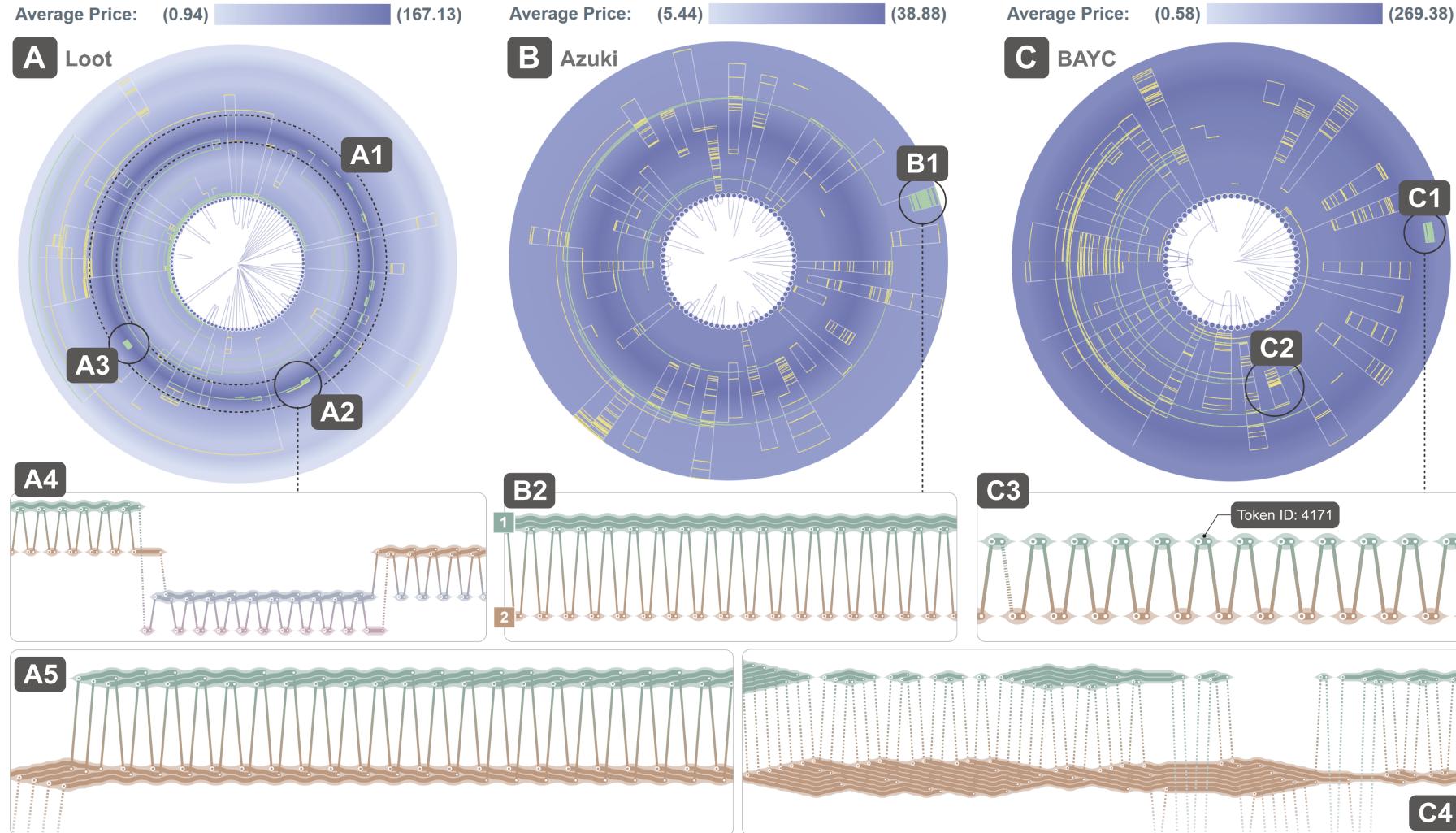
- Lessons learned:
 - Group of addresses > Individual addresses.
 - Different addresses have different tasks.
 - Not all wash trading are “harmful”.
- Design considerations for novices users:
 - Straightforward visual design (market risk -> height of flows);
 - Overview first, Details on demand;

Generalization

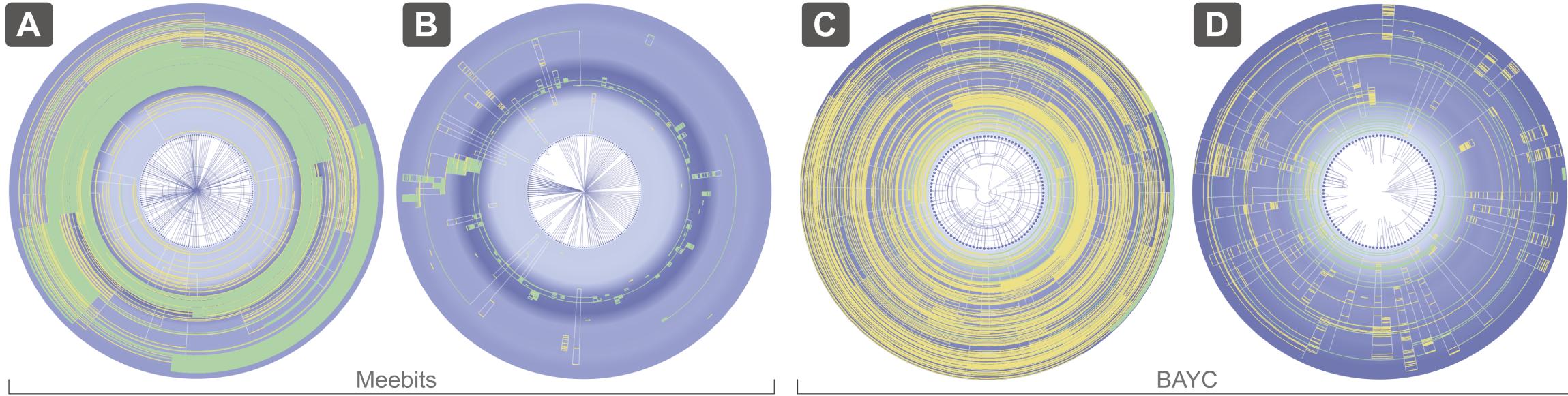
- Workflow => Other frauds in cryptocurrency markets:
 - e.g. money laundering
- NFTDisk => Traditional financial market:
 - e.g. stocks and bonds
- NFTDisk => Other abnormal online activities involving different participants:
 - e.g. Political Astroturfing

Case 2

Wash Trading Enhanced by Trading Rewards but Discouraged by Royalties



Address Reordering



Amount of transactions => distance matrix of addresses

Hierarchy clustering => clustering tree => optimal leaf ordering algorithm

Suspicious Score

$$S = 1 - \frac{N}{M}$$

where M is the number of transactions between the two addresses, and N is the number of unique NFTs involved in these transactions. The higher the suspicious score, the more likely the address pair is to collude. If each transaction from a pair of addresses includes a different NFT, then their suspicious score is zero.