
Unveiling the Dynamics of Ethereum Token Transactions: A Hypergraph-Based Approach

Project Report

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Declaration

I, Neeharika Telu (Roll No: CS21B1029), hereby declare that this report entitled “Unveiling the Dynamics of Ethereum Token Transactions: A Hypergraph-Based Approach”, submitted to the Indian Institute of Information Technology Raichur towards partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering, is an original work carried out by me under the supervision of Dr. Priodyuti Pradhan and has not formed the basis for the award of any degree or diploma in this or any other institution or university.

I have sincerely tried to uphold academic ethics and honesty. Whenever external information, statements, or results are used, they have been duly acknowledged and cited.

Place: Raichur
Date: April 26, 2025

Neeharika Telu

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1 Abstract

This report presents a novel approach to modeling ERC-721 token transactions on the Ethereum blockchain using hypergraphs. By leveraging a comprehensive dataset from X-Block ETH, we explore the dynamics of token transfers and the relationships between wallets. Traditional graph methods, while useful, often overlook complex interactions and temporal changes within the data. In contrast, our hypergraph model provides deeper insights into the network of token transactions, revealing unique patterns and facilitating a better understanding of wallet interactions. Our approach captures the multifaceted relationships where multiple wallets interact with a single token or vice versa, going beyond pairwise connections. Additionally, by incorporating temporal data, the hypergraph model highlights how wallet interactions evolve over time.

2 Introduction

Over the years, networks have been extensively investigated and have successfully provided insights into the structure and dynamics of physical [1], biological [2, 3, 5, 4], social [6, 7] and several other natural systems [8].

The growing complexity of networks has led researchers to analyze optimal structures and strategies for studying the diverse structural properties and dynamic behaviors of complex networks. Prominent examples relevant to this analysis are interconnected networks represented by multilayer networks [9, 10] and higher-order interactions [11, 12, 13, 14], which are investigated using hypergraphs and simplicial complexes.

Higher-order interactions represent the connections among two or more than two nodes simultaneously in complex systems. Such interactions can be modeled as hyperedges analogous to edges in conventional graphs or simplices in simplicial complexes. Simplicial complex is a specific type of hypergraph with an inclusion property: For a triadic interaction (i, j, k) to exist, the corresponding dyadic interactions (i, j) , (i, k) and (j, k) must also be present. In this article, we make use of hypergraphs for our analysis.

Various fields have witnessed the existence of higher-order interactions such as the human brain [15], collaboration networks [17], species interactions [16], cellular networks [18], and drug combinations [19]. Notably, in several real-world networks, presence of higher-order interactions has been found to give new insights, for example, in [20], authors developed a novel method called high-order

functional connectivity, which captures interactions among three or more brain regions across various spatiotemporal scales. This method was applied to detailed EEG and fMRI characterizations of neurodegenerative conditions.

Faes et al. [21] introduced the O-information rate (OIR) metric to evaluate higher-order interactions in multivariate time series. This approach was applied to physiological networks, such as heart period, respiratory variability, and arterial pressure in healthy subjects, as well as brain networks described by electrocorticographic signals in animal experiments during anesthesia. Moreover, a study proposed STHAN-SR, a neural hypergraph architecture for stock selection that models complex relationships between stocks using a hypergraph and temporal Hawkes attention mechanism, resulting in a new spatiotemporal attention [22]. In [23], authors conducted neuronal studies revealing that while pair-wise interactions between neurons explain population responses in sensory areas, higher-order interactions are necessary to explain responses in executive areas involved in decision-making and actions.

Santoro et al. [24] analyzed multivariate time series to uncover higher-order patterns in brain functional activity, epidemics, and financial markets. Additionally, a multivariate signal processing technique was developed to construct higher-order networks from time series, which was applied to resting fMRI signals to identify higher-order communications between different brain regions.

Also, these group interactions give rise to new collective phenomena, including synchronization [25, 26], contagion dynamics [27, 28], diffusion processes [29], and evolutionary games [30, 31]. For example, in the evolutionary dynamics of public good games on hypergraph, it is found that overlap between hyperedges tend to foster cooperative outcomes and the heterogeneity of hyperedges promotes cooperation [32]. Burgio et. al [33] studied the susceptible-infectious-susceptible (SIS) process on a hypergraph and demonstrated that overlap between three body interactions lowers the critical point and

produces smaller spreads.

Cencetti et al. examined the formation and evaluation of higher-order organizations in temporal networks by studying five social network datasets from various social contexts [34].

3 Pre-requisites

3.1 Blockchain

A blockchain is a decentralized ledger that involves blocks of data, usually with several transactions, a date, the previous block's hash, and a nonce for hash verification. Because blocks are encrypted, it means they are linked through their unique and unalterable hash values, thus ensuring integrity. A consensus mechanism validates transactions through a network, where nodes agree on whether the block is valid before adding it to the chain [35]. This process secures the blockchain, preventing any form of tampering, which enables trust in peer-to-peer asset transfers, as seen in Bitcoin, whereby miners validate blocks and are rewarded with cryptocurrency [36].

3.2 Ethereum

Ethereum, proposed in Vitalik Buterin's paper [37], addresses several limitations of Bitcoin's scripting language. Its chief contributions include full Turing-completeness, supporting all kinds of computations, including loops. More importantly, it improves the structure of a blockchain by allowing for transaction states and other such improvements. Abstractly, it provides an additional layer where users can define customized rules for ownership and transaction formats and also state transition functions via smart contracts-cryptographic rules executed when certain conditions are met [38].

3.3 Non Fungible Token

Non Fungible Token (NFTs) are digital tokens issued on the Ethereum blockchain, similar to Bitcoin, in that they're "minted" and sold. But unlike Bitcoin, which is "fungible," that is, indistinguishable from another bitcoin, NFTs are "non-fungible," that is each token unique. This uniqueness assigns a property right over digital assets, for instance Beeple's artwork. Anyone can view Beeple's "Everydays—The First 5,000 Days"; only the owner of the associated NFT can make an ownership claim.

This dynamic introduces exclusivity into digital art. The NFT is recorded on the immutable Ethereum blockchain after being minted, which proves ownership of the art. While digital art can be looked at, copied, and shared, NFTs ensure that ownership cannot be faked, enabling true exclusive ownership of digital art, a phenomenon previously unthinkable [39].

3.4 ERC-721

The ERC-721 Non-Fungible Token (NFT) Standard [40] proposes a structure to represent one-of-a-kind tokens that are not interchangeable within the Ethereum blockchain. In the case of ERC-20 tokens, their uniqueness and interchangeability come to an end, ERC-721 on the other hand has no crops and it plays the role of managing unique asset properties. They afford atomic management for ownership of each unique digital asset, thus finding usefulness with 'one of a kind' digital objects such as NFTs, games, or intellectual property. By default, the standard states that the American Public policy has ten basic functions and three events which should be observed.

ERC-721 standard tokens were created and distributed via smart contracts and placed on the Ethereum network. The standard is free and open by nature, which means that it can be leveraged when creating non-fungible tokens that are aimed at specific digital as-

sets/objects, which can be owned individually and have historical backgrounds. An application of ERC-721 tokens is CryptoKitties which are internet pets available for auction. Thirdly, the ERC 721 standard lays out basic provisions for creating, issuing, managing, transferring and trading of these specific types of tokens, thus introducing new digital forms of scarcity and asset representation [41].

3.5 Smart and Non-Smart Contracts

In digital systems, transactions and agreements between parties can be handled either manually or through automated processes. These two approaches are broadly categorized as non-smart contracts and smart contracts, respectively.

3.5.1 Non-Smart Contracts

Non-smart contracts refer to traditional, manual methods of executing transactions or agreements. In such systems, human intervention is required at each step to initiate, authorize, and complete the process. The actions depend entirely on the users' decisions and manual inputs. These contracts lack automation and require the parties involved to actively participate in every stage of execution. This approach is similar to how conventional payments or physical agreements work — where the outcome is dependent on explicit user approval and execution.

3.5.2 Smart Contracts

Smart contracts, on the other hand, are self-executing digital contracts where the terms of the agreement are written in code and automatically enforced by the system. Once deployed, a smart contract runs on a blockchain and performs predefined actions when certain conditions are met — without needing manual approval each time. This brings automation, trust, and efficiency into the transac-

tion process. Smart contracts reduce the need for intermediaries and minimize the chances of human error or intentional manipulation.

3.5.3 Key Differences

Automation

Smart contracts operate automatically, while non-smart contracts require manual intervention.

Trust

Smart contracts are executed based on code and cannot be altered once deployed, offering higher reliability.

Efficiency

Smart contracts execute instantly once conditions are met, whereas non-smart contracts may be delayed due to human dependency.

3.6 Hypergraph

A hypergraph is a generalization of a regular graph. While in a standard graph, each edge connects exactly two nodes, in a hypergraph, an edge can connect any number of nodes — not just two. Hypergraphs are useful in scenarios where relationships involve more than two elements.

H denoted by $H = (V; E = (e_i)_{i \in I})$ on a finite set V is a family $(e_i)_{i \in I}$, where I is a finite set of indexes, of subsets of V called hyperedges. Sometimes V is denoted by $V(H)$ and E by $E(H)$ [42].

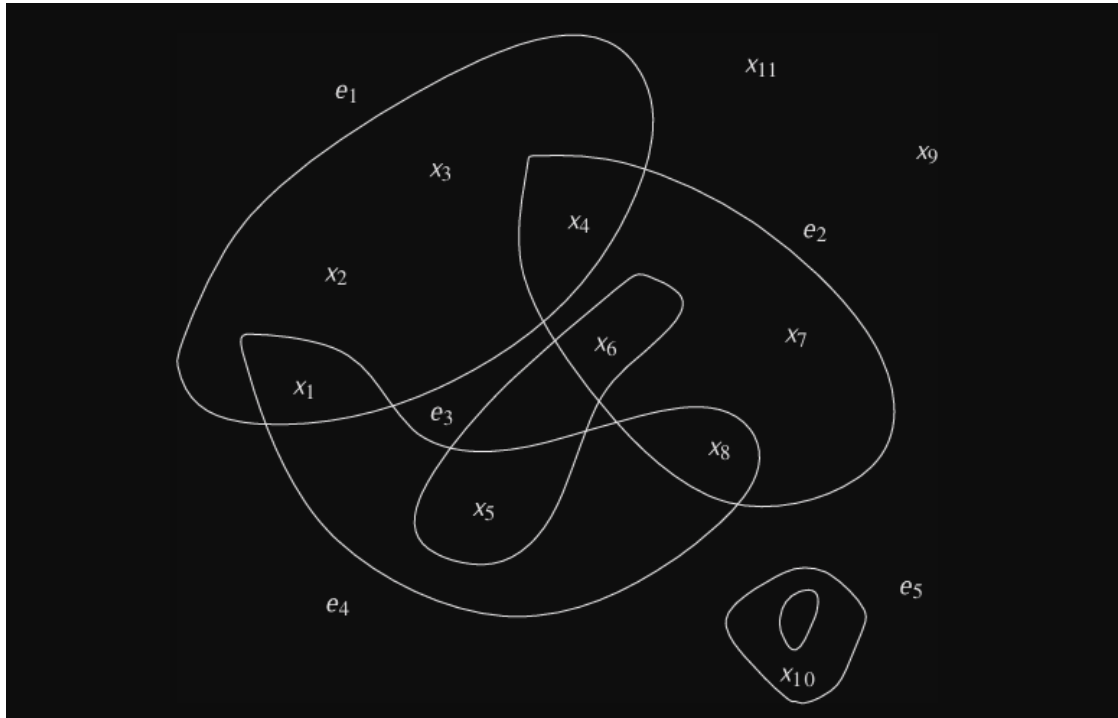


Figure 3.1: The hypergraph H above has 11 vertices, 5 hyperedges e_5 , and 2 isolated vertices: x_{11}, x_9 . The degree of x_1 is 2 [42].

4 ERC721 Token Transaction Data and Network Modeling

4.1 Transaction Data sets - XBLOCK-ETH [43]

The dataset comprises detailed records of ERC-721 token transactions, which are the foundation for non-fungible tokens (NFTs) on the Ethereum blockchain. Each entry within the dataset provides essential information, including the block number (which indicates where the transaction is recorded on the blockchain), a timestamp (showing when the transaction took place), a unique transaction hash (serving as an identifier), and the addresses of both the sender and recipient.

Additionally, the dataset specifies whether these addresses belong to smart contracts or externally owned accounts, adding another layer of context to the transactions. Spanning from 2015 to 2024, this dataset offers a rich temporal range, enabling analysis of trends and developments in the NFT market over nearly a decade.

4.2 Data Preprocessing

Our analysis began with the preprocessing of the X-Block ETH dataset.

4.2.1 Data Downloading

The initial step in the data preparation procedure was sourcing the needed transaction data found on repository X-Block ETH that contained records of Ethereum transactions. The information contained several key features such as the transaction timing, a respective block to the transaction, the addresses involved and the type of token.

blockNumber	timestamp	transactionHash	tokenAddress	from	to	fromIsContract	toIsContract	tokenId
1001165	1455424860	0x1d11b3ea5593ec	0x55b9a11c2e835	0x38150290c18	0x3d2068aeb96	0	0	200000000
1001165	1455424860	0x1d11b3ea5593ec	0x55b9a11c2e835	0x38150290c18	0x5d2c24efac49	0	1	0
1003181	1455460299	0x26a30aa663f6e1	0x55b9a11c2e835	0x38150290c18	0x3d2068aeb96	0	0	500000000
1003181	1455460299	0x26a30aa663f6e1	0x55b9a11c2e835	0x38150290c18	0x5d2c24efac49	0	1	0
1003393	1455463847	0xc0db923ac0c6d7	0x55b9a11c2e835	0x3d2068aeb96	0xb51446cc429	0	0	100000000
1003393	1455463847	0xc0db923ac0c6d7	0x55b9a11c2e835	0x3d2068aeb96	0x5d2c24efac49	0	1	130000
1005878	1455505636	0x113de15964f857	0x55b9a11c2e835	0x38150290c18	0xc0cfc0969d0d	0	0	1000000000
1005878	1455505636	0x113de15964f857	0x55b9a11c2e835	0x38150290c18	0x5d2c24efac49	0	1	0
1005946	1455506683	0x09581f238af3eb	0x55b9a11c2e835	0xc0cfc0969d0d	0xa220568ace9	0	0	1000000000
1005946	1455506683	0x09581f238af3eb	0x55b9a11c2e835	0xc0cfc0969d0d	0x5d2c24efac49	0	1	130000
1006034	1455508426	0x637e4263f7825d	0x55b9a11c2e835	0x38150290c18	0xa220568ace9	0	0	200000000
1006034	1455508426	0x637e4263f7825d	0x55b9a11c2e835	0x38150290c18	0x5d2c24efac49	0	1	0
1006046	1455508554	0x5eac9cbd9cae1t	0x55b9a11c2e835	0xc0cfc0969d0d	0xa220568ace9	0	0	898000000
1006046	1455508554	0x5eac9cbd9cae1t	0x55b9a11c2e835	0xc0cfc0969d0d	0x5d2c24efac49	0	1	1167400
1006059	1455508793	0xc71da93bc6643	0x55b9a11c2e835	0x38150290c18	0xa220568ace9	0	0	4000000000
1006059	1455508793	0xc71da93bc6643	0x55b9a11c2e835	0x38150290c18	0x5d2c24efac49	0	1	0
1007626	1455536210	0x6c6729b405473	0x55b9a11c2e835	0x38150290c18	0xad917335252	0	0	200000000
1007626	1455536210	0x6c6729b405473	0x55b9a11c2e835	0x38150290c18	0x5d2c24efac49	0	1	0
1007645	1455536477	0x0a67fa2e1500f4	0x55b9a11c2e835	0x38150290c18	0xad917335252	0	0	1800000000
1007645	1455536477	0x0a67fa2e1500f4	0x55b9a11c2e835	0x38150290c18	0x5d2c24efac49	0	1	0
1007784	1455539020	0x8d55d21c2e77a	0x55b9a11c2e835	0x38150290c18	0xad917335252	0	0	8000000000
1007784	1455539020	0x8d55d21c2e77a	0x55b9a11c2e835	0x38150290c18	0x5d2c24efac49	0	1	0
1008013	1455542892	0xb3a5580191a1c	0x55b9a11c2e835	0x9ac937835f6e	0x5d2c24efac49	0	1	411
1008013	1455542892	0xb3a5580191a1c	0x55b9a11c2e835	0x38150290c18	0x9ac937835f6e	0	0	1000000000
1008013	1455542892	0xb3a5580191a1c	0x55b9a11c2e835	0x38150290c18	0x5d2c24efac49	0	1	0

Figure 4.1: Downloaded Data From XBlock-Eth

4.2.2 Unix to Human Readable Timestamp

One of the earliest activities in the preprocessing process was to manage the timestamps which varied among other formats supposedly stored in Unix epoch. In order to make the reader's work easier, these timestamps were formatted in an easier to comprehend (YY-MM-DD) thereby ensuring that the information in the dataset would be well understood not only by humans but also by the algorithms which process it.

4.2.3 Dividing Data into Daywise Files

On completion of the conversion of currencies, the data set was arranged in the form of day wise files. This was done to limit the analysis of the transactions to the specific dates, making it easier to analyze the transactional trends and patterns on a daily basis. All these daywise files were also dated meaning that every single file was clearly marked with the date so that the information was organized properly and could be retrieved easily for more work.

Each daywise file contained a few key columns which were designed to capture important details about the transactions. More specifically, these included the date and time stamp of each transaction, the block in which the transaction's records were added, the respective addresses of the different parties in the transaction (from, to), the address of the token which typified the transfer, and whether or not the addresses that transacted were smart contracts. These flags were of utmost importance as they explained how different addresses operate within their blockchain network.

The last two columns-venturing information on which address was or was not a smart contract remained constant over the course of the processing.

4.2.4 Address Labelling

The 64-bit numerical addresses in the dataset presented a challenge that needed to be addressed in a special way. To further enhance the understanding and make the dataset more interpretable, these numerical addresses were converted into appropriate labels with a junction of a dictionary. As such, it aided to comprehend how the addresses were interconnected in addition to creating a rough outline of the distributions or outliers observed in the changes of the data i.e the mentioned occurrences of certain transfers of tokens to particular wallets or smart contracts from the available ones.

blockNumber	timestamp	transactionHash	tokenAddress	from	to	fromIsContract	toIsContract	tokenId
5918558	2018-07-07 0:01	0xeb8b537664ad398	0x06012c8cf97bead5	0x4fabda075e15e9	0x0acb5378a71	0	0	824413
5918560	2018-07-07 0:01	0x8ac506f81242adcc	0x06012c8cf97bead5	0x9eec7e6391071	0xfa580941ec47	0	0	556396
5918567	2018-07-07 0:03	0xc37b4a2b5c0a979	0x7fddc2a1e52f10c2e	0x1e74456cc75e4e	0x2842a67ce34	0	1	3929
5918570	2018-07-07 0:04	0x2a1cf54f8a812cd3	0x06012c8cf97bead5	0xc7af99fe5513ebf	0x4fabda075e15	1	0	825908
5918581	2018-07-07 0:05	0xee2280d9243df7e	0x06012c8cf97bead5	0x4fabda075e15e9	0xb1690c08e21	0	1	831457
5918583	2018-07-07 0:06	0x2deb5153f5799911	0x7fddc2a1e52f10c2e	0x54133617ad48a	0x92cace836fa2	0	1	3449
5918584	2018-07-07 0:06	0x1a4f17fa7394388f	0x06012c8cf97bead5	0x0000000000000000	0x442dccc6e84	0	0	833692
5918584	2018-07-07 0:06	0x2001c1e251ee963	0x06012c8cf97bead5	0x0000000000000000	0x68b42e44079	0	0	833693
5918584	2018-07-07 0:06	0x803b1644d2d38f8	0x06012c8cf97bead5	0x0000000000000000	0x7891f796a5d4	0	0	833694
5918584	2018-07-07 0:06	0x5555e5bc64204a3	0x06012c8cf97bead5	0x0000000000000000	0x22d1a32a0be	0	0	833695
5918584	2018-07-07 0:06	0x67a495b4f359d78	0x06012c8cf97bead5	0x0000000000000000	0x820c0557307	0	0	833696
5918584	2018-07-07 0:06	0x1a001ce852f4dc8	0x06012c8cf97bead5	0x0000000000000000	0xc7a024df3876	0	0	833697
5918584	2018-07-07 0:06	0x2023c3fa1d92e7f6	0x06012c8cf97bead5	0x0000000000000000	0x06012c8cf97b	0	1	833698
5918584	2018-07-07 0:06	0x2023c3fa1d92e7f6	0x06012c8cf97bead5	0x06012c8cf97bea	0xb1690c08e21	1	1	833698
5918586	2018-07-07 0:06	0xa225f3cef80c37c2	0x06012c8cf97bead5	0x4fabda075e15e9	0xb1690c08e21	0	1	830720
5918587	2018-07-07 0:07	0x9c991844105e681	0x06012c8cf97bead5	0x4fabda075e15e9	0xb1690c08e21	0	1	830716
5918587	2018-07-07 0:07	0xaf2aeb1b040cb0fc	0x06012c8cf97bead5	0xb1690c08e213a	0x5be7d57e9b1	1	0	833072
5918591	2018-07-07 0:08	0x21aa77639430734	0x06012c8cf97bead5	0x4fabda075e15e9	0xb1690c08e21	0	1	829836
5918592	2018-07-07 0:08	0x507e9c6f5150c1a	0x1a94fce7ef36bc90	0x0000000000000000	0x2e4ee826597	0	0	9521
5918594	2018-07-07 0:08	0xef0637db5d13a01	0x06012c8cf97bead5	0x4fabda075e15e9	0xb1690c08e21	0	1	828948
5918599	2018-07-07 0:10	0xb129c21b597642d	0x06012c8cf97bead5	0x4fabda075e15e9	0xb1690c08e21	0	1	828570
5918600	2018-07-07 0:10	0x746a38f26b80be8	0x06012c8cf97bead5	0x4fabda075e15e9	0xb1690c08e21	0	1	828196
5918603	2018-07-07 0:10	0x5b1d6fc19252734	0x7fddc2a1e52f10c2e	0x5ab10735fd42ec	0x2842a67ce34	0	1	4065
5918604	2018-07-07 0:10	0x2a2738c45a5fc80	0x06012c8cf97bead5	0x4fabda075e15e9	0xb1690c08e21	0	1	828185
5918604	2018-07-07 0:10	0xe3bdda39c984755	0x06012c8cf97bead5	0x4fabda075e15e9	0xb1690c08e21	0	1	828179

Figure 4.2: Daywise Splitting

4.2.5 Hypergraph Format

We stored the Hypergraph in JSON file format, where the Key will be a hyperedge, and the values present in the Key will be the nodes associated with the hyperedge.

Overall, the preprocessing steps were designed to ensure the dataset was clean, well-structured, and ready for further analysis. This approach allowed for easy extraction of meaningful insights from the transaction data and laid the foundation for more complex analyses, such as network analysis, node degree calculations, and hypergraph modeling.

timestamp	fromLabel	toLabel	tokenAddressLabel	fromIsContract	toIsContract	tokenId
2018-07-07 00:01:25	71594	90964	53	0	0	824413
2018-07-07 00:01:50	98051	101339	53	0	0	556396
2018-07-07 00:03:07	87786	101274	381	0	1	3929
2018-07-07 00:04:04	828	71594	53	1	0	825908
2018-07-07 00:05:22	71594	825	53	0	1	831457
2018-07-07 00:06:00	82513	93145	381	0	1	3449
2018-07-07 00:06:06	1179	825	53	1	1	833698
2018-07-07 00:06:49	71594	825	53	0	1	830720
2018-07-07 00:07:33	71594	825	53	0	1	830716
2018-07-07 00:07:33	825	71036	53	1	0	833072
2018-07-07 00:08:12	71594	825	53	0	1	829836
2018-07-07 00:08:46	71594	825	53	0	1	828948
2018-07-07 00:10:01	71594	825	53	0	1	828570

Figure 4.3: Labelled Data

```
{
  "24": [99, 86582],
  "53": [37889, 98051, 91143, 94220, 10005, 65048, 21017, 22042, 65820, 64031, 90657, 70179, 14118, 21544, 22314, 14894, 93743, 815, 28465, 67638, 825, 828, 40514, 74564, 94539, 68684, 71758, 68686, 12879, 85840, 33104, 90964, 50004, 74844, 66143, 80736, 70753, 90737, 65398, 75384, 83833, 72316, 71036, 12157, 87423, 93570, 81284, 67717, 41094, 65162, 65164, 72844, 76430, 75923, 6292, 93844, 91540, 101270, 1179, 86687, 66720, 8609, 101281, 66725, 28070, 95144, 92842, 71594, 95918, 94894, 50862, 65455, 53681, 101044, 91067, 30142, 101311, 101315, 40396, 16333, 41421, 92376, 72409, 101337, 55515, 101339, 69341, 101340, 101342, 101343, 70881, 101345, 101346, 101348, 101349, 101350, 101351, 101352, 6632, 59114, 2283, 101354, 101355, 101356, 101357, 101360, 8945, 93431, 65021],
  "69": [95348, 56823],
  "146": [66720, 69399],
  "266": [72547, 72572, 72947],
  "381": [87763, 100485, 101256, 84617, 94989, 84625, 101274, 83486, 87753, 82476, 85934, 100398, 82992, 100787, 82995, 85814, 82873, 100028, 101309, 101310, 82882, 82630, 85703, 82631, 87752, 87754, 87755, 87756, 87757, 87758, 87759, 87760, 82513, 87762, 87761, 87764, 87765, 93396, 87767, 87768, 93145, 87770, 87771, 87772, 87773, 87774, 82911, 87775, 87776, 87778, 87779, 87777, 87766, 87780, 87786, 87787, 88829, 97790],
  "396": [101330, 12157, 84269],
  "440": [94273, 93697, 95235, 89961, 101353, 92141, 101277, 95471, 95856, 90778, 95964, 87965, 75743],
  "463": [88512, 85840, 90691, 91067, 83436, 12157, 88799],
  "484": [101248, 90816, 92228, 100486, 100429, 94993, 6292, 101338, 95394, 101347, 100646, 95529, 94961, 95541, 94775, 92092, 92093],
  "493": [94265, 93382, 85134, 93383],
  "512": [100617, 99062, 99599],
  "519": [100420, 58180, 88565, 74264, 65769, 94331, 93406]
}
```

Figure 4.4: Storing Hypergraphs as JSON Files

hypergraph_2018-07-07

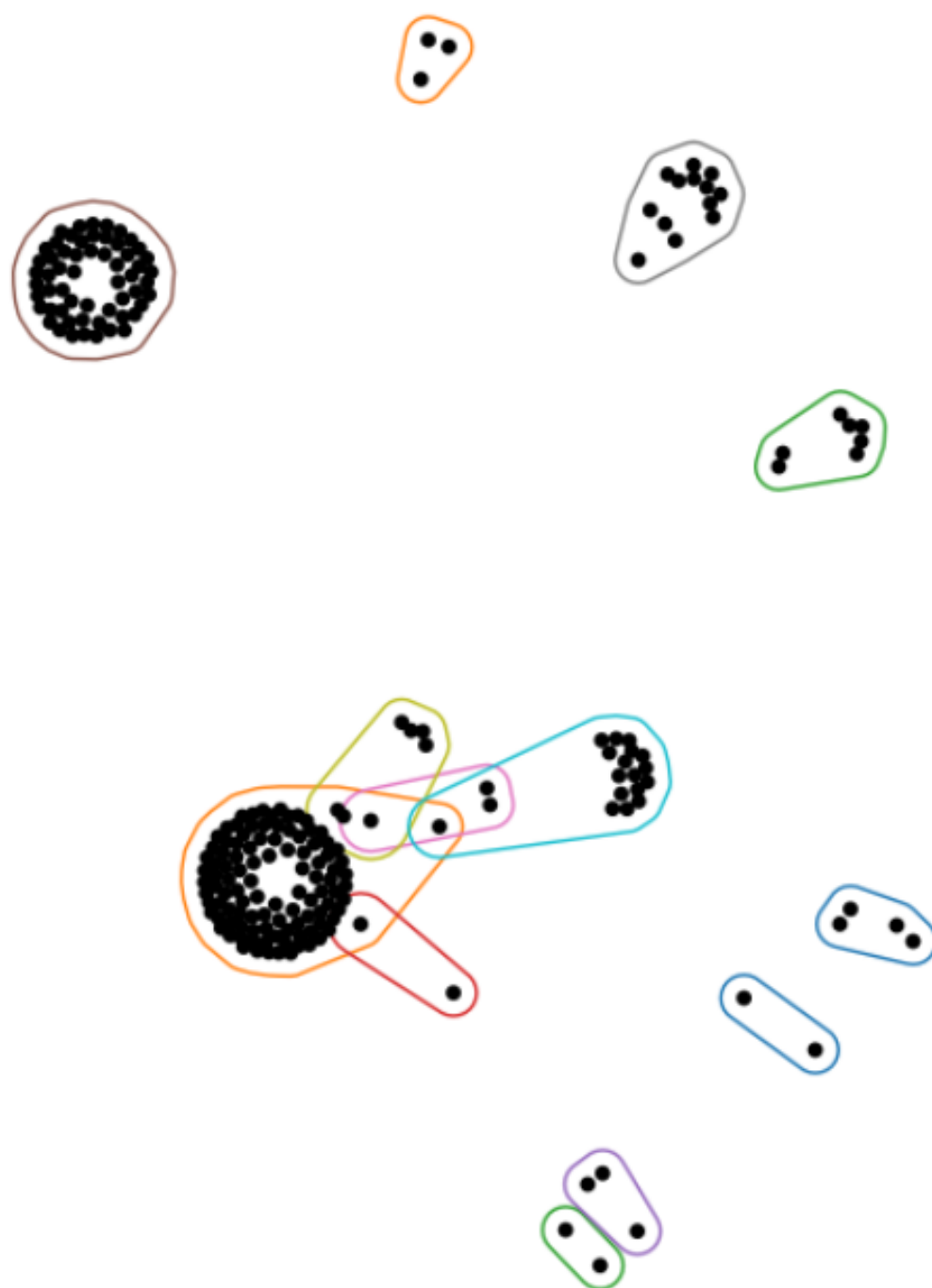


Figure 4.5: Visualisation of A Day's Hypergraph

4.3 Analysis Using Traditional Graphs

To understand the relationships between wallets and transactions, we implemented a series of analyses. We developed a script to calculate the total number of unique wallets (nodes) involved in the transactions, with the results represented on a log scale for better visualization. Following this, we plotted the number of unique nodes on a daywise basis to observe participation trends over time. Additionally, we represented daywise transactions with edges, illustrating the pairwise connections between nodes. To further enhance our analysis, we also plotted daywise unique edges, which allowed us to visualize the distinct transactions occurring each day.

4.4 Limitations of Traditional Graphs

While the traditional graph methods provided valuable insights into the number of wallets and transactions, they fell short in capturing several critical aspects. For example, they could not adequately reveal how many wallets were involved in token transfers or how these interactions changed over time. Additionally, traditional graphs often struggle to represent higher-order relationships, where a single transaction can involve multiple participants simultaneously. This limitation highlighted the need for a more sophisticated approach.

4.5 Introduction to Hypergraphs

Hypergraphs extend the concept of traditional graphs by allowing edges to connect any number of vertices, rather than just pairs. In a hypergraph, a hyperedge can link multiple nodes, enabling a more nuanced representation of complex relationships. Examples include Group conversations in social networks (one message to many people),

Co-authorship networks (one paper authored by multiple people),

Transaction data (one transaction involving many accounts),
Tagging systems (an item tagged with multiple categories). This framework is particularly advantageous in the context of ERC-721 transactions, where a single token transfer may involve several participants.

4.5.1 Advantages of Hypergraphs over Traditional Graphs

Utilizing hypergraphs in our analysis offers a more comprehensive representation of interactions. First, hypergraphs can effectively capture multi-way relationships, showcasing situations where multiple wallets collaborate to transfer a single token. Additionally, they allow us to observe the evolution of these relationships over time, unveiling patterns that traditional graphs may overlook. Finally, by treating tokens as hyperedges, we can assess the collective influence of multiple wallets on token transfers, yielding valuable insights into collaboration and community dynamics within the NFT ecosystem.

4.6 Token as Hyperedges

In our model, each token was treated as a hyperedge, with the wallets involved in the transfer of that token represented as nodes connected to the hyperedge. We conducted the following analyses: Tokens vs. Days: We plotted the number of tokens transferred against days to visualize trends over time. Unique Tokens: We examined the unique tokens traded daily. Node Degree Calculation: The degree of each node (the number of tokens traded by that wallet on a particular day) was calculated daily. Degree Centrality: We calculated the degree centrality for nodes each day, providing insights into the most active wallets. 3.4 Analysis of Hyperedges We explored the number of nodes involved in each token transfer and calculated the number of 1-hyperedges, 2-hyperedges, and so on, on a daywise basis. Over the period from 2015 to 2024, we identified a total of 4,000 hyperedges, with a maximum of 130,000 nodes involved in one hyperedge.

4.6.1 Daywise Hypergraph Creation

To track and analyze the evolution of ERC-721 transactions, day-wise hypergraphs were created based on transaction data, with each hyperedge representing a unique token. For each day, the total number of hyperedges (tokens) was computed, and the nodes involved in token transfers were identified.

4.6.2 Temporal Evolution of Nodes, Edges, and Hyperedges

Daily changes in the counts of nodes, edges, and hyperedges were analyzed to observe shifts in transaction activity over time. From 2015 to October 2017, ERC-721 transactions and token transfers between wallets were minimal. This low-activity period provided limited information value and was thus excluded from further analysis. The focus was placed on the more active period from 2017 to 2024, resulting in a dataset more relevant for hypergraph-based analysis.

4.6.3 Degree of a Node

The degree of a node, representing the number of tokens a wallet transfers in a given day, was calculated for each node. For each day, the node with the highest degree was identified as the most active, highlighting the account with the most token transfers for that day. Analyzing daily maximum degrees helped monitor activity peaks and provided insights into particularly active wallets. When extracting maximum-degree information, efforts were made to classify the node type as either a smart contract or an externally owned account. During this process, a few nodes were found to exhibit both types of behavior, an anomaly in the Ethereum system.

4.6.4 Node Type Classification

To better understand node roles, nodes were categorized as either externally owned accounts (EOAs) or smart contracts. EOAs represent

individual users, while smart contracts automate complex transactions. Some nodes appeared as both EOAs and smart contracts while observing the node behavior which has maximum degree, which is not possible within Ethereum’s system. Removing these misclassified nodes improved data quality, clarifying the distinction between regular user accounts and contract-driven addresses.

4.6.5 Null Address Handling

The null address, commonly used as a placeholder or for testing purposes, frequently appeared in transactions when extracting information on nodes with maximum degrees. Its presence affected maximum degree calculations by introducing a non-participant entity. Removing the null address allowed the dataset to more accurately reflect real user interactions. After removing the null address and nodes misidentified as both smart contracts and regular accounts, the dataset became cleaner and more representative of actual interactions.

4.6.6 Hyperedge Classification by Node Count

Hyperedges were classified by the number of nodes involved. For example, a 1-hyperedge involved a single node, while a 2-hyperedge represented token transfers between two nodes. Analyzing these hyperedges revealed a range of transaction types, from single-wallet actions to multi-wallet interactions. After data cleaning, the maximum hyperedge count reached 45,833, whereas it was initially as high as 126,455 when the null address was included.

Hyperedge Classification by Node Count Hyperedges in this network capture token transactions, with the node count indicating transaction types.

1-Hyperedge (Self-Transaction)

This is a single-node transaction, where a node transfers tokens to itself, usually for organizational purposes or automated tasks. Example: Imagine Ravi transferring tokens from one of his wallet accounts to another for internal management.

2-Hyperedge (Standard Two-Node Transfer)

This is the typical transaction where one node sends tokens directly to another node, involving two participants. Example: If Priya sends tokens to Chintu, this forms a 2-hyperedge, with a simple sender-receiver dynamic.

3-Hyperedge (Three-Node Chain)

A three-node hyperedge represents transactions involving three distinct nodes, often seen in multi-step transactions. Example: In a scenario where Priya sends tokens to Bhuvan, who then forwards them to Chintu, this forms a 3-hyperedge.

n-Hyperedge (Multi-Node Transaction)

Transactions with four or more nodes represent complex, multi-party transactions, common in pooled investments or decentralized finance. Example: For instance, if multiple investors pool funds into a shared fund, this can form an n-hyperedge, indicating large-scale, multi-participant involvement.

Statistics

Total Number of Unique Nodes - 4901602

Total number of Unique Transactions - 67014090

Total number of tokens - 147320

Total number of k-hyperedges - 3261

Maximum size of the k-hyperedge - 45833 (wallets involved)

5 Temporal Evolution of Nodes, Edges, and Hyperedges

To study the dynamics of ERC-721 token transactions over time, we constructed daily hypergraphs from transaction records. In this model, each unique token is represented as a hyperedge, while the wallets involved in transferring the token on that particular day act as nodes connected by the hyperedge.

Daily counts of nodes, edges, and hyperedges were analyzed to observe variations in transaction activity. The degree of a node, defined as the number of tokens (hyperedges) a wallet participates in during a specific day, was calculated. By labeling and parsing each day-wise transaction file, we identified the number of unique wallets (nodes) active each day. Additionally, we tracked the number of new wallets introduced each day—i.e., wallets appearing for the first time and not seen in any previous days. Across the dataset (2017 to 2024), a total of 49,01,602 unique wallets were identified.

For each day, we computed the node with the highest degree, indicating the wallet most active in token transfers. This helped identify peak activity periods and high-volume participants. We also classified each node with the highest degree as either a smart contract or an externally owned account (EOA). In doing so, we observed that some wallets exhibited behavior consistent with both types.

Constructing hypergraphs for each day provided a clear structure of wallet participation in token transfers. Analyzing node degrees revealed the presence of "null addresses," often involved in large numbers of transactions, typically used for testing or dumping. The node degree distribution followed a power law, where most nodes had low

degrees, while a small number of nodes had significantly high degrees, indicating that only a few wallets were involved in multiple token transfers (Figure 5).

4.2 Day-wise Hypergraph Construction

For each day from 2017 to 2024, we examined the number of nodes involved in each token transfer and classified the corresponding hyperedges. Hyperedges were categorized based on the number of participating nodes: 1-hyperedge (single-node), 2-hyperedge (two-node), and so forth (Figure 7). We observed a total of 4000 distinct hyperedges, with some involving up to a maximum of 130,000 nodes in a single hyperedge. The distribution of hyperedge sizes over time was also visualized (Figure 8).

A total of 3,261 k -hyperedges (hyperedges involving k nodes) were identified. The maximum size of a k -hyperedge was 45,833 wallets. The frequency of k -hyperedges decreased as the number of nodes increased, following a power law. This means large hyperedges were rarer, while smaller hyperedges were more common. Such distribution hints at the rarity of large-scale, multi-wallet transactions.

Community detection was performed to identify repeated transaction patterns where the same set of wallets transacted the same token on multiple days.

4.3 Hyperedge Classification by Node Count

Hyperedges were further classified based on the number of participating nodes to understand the complexity of transactions:

- 1-Hyperedge: Represents a self-transaction where a wallet transfers tokens to itself. This may occur for organizational reasons or automated activities.
- 2-Hyperedge: The standard transaction where one wallet sends tokens to another.
- 3-Hyperedge: Represents a transaction involving three nodes, commonly found in multi-step transfers (e.g., $A \rightarrow B \rightarrow C$).
- k -Hyperedge: Involves four or more nodes, indicating complex, large-scale transactions. These are typical in pooled investments or DeFi protocols.

After cleaning the data by removing null addresses, the maximum

hyperedge count observed was 45,833 (initially as high as 126,455).

4.4 Recurring Multi-Node Interactions

Recurring hyperedges involving the same group of nodes appearing on multiple days were analyzed. For instance: - Token 1: Nodes (2, 96, 90754) interacted on 2018-05-20, 2018-09-15, and 2018-09-30. - Token 21: Nodes (704, 34515, 56173) interacted on 2018-01-19 and 2018-02-23.

These interactions reveal stable trading behavior or partnerships. Repeated node group interactions signal potential communities within the blockchain network. Tracking these can help uncover user clusters with shared interests or coordinated activity.

We plotted trends such as tokens transferred per day and the count of unique tokens traded daily. Daily hypergraphs from 2017 to 2024 were stored in JSON format. Example entry: "2017-03-06": "10": [33, 17] ', where 10 is a token (hyperedge) and 33, 17 are participating wallets (nodes).

To study recurring hyperedges, we focused on k-hyperedges that appeared multiple times. For instance, a 3-hyperedge appearing on several dates suggests a trio of wallets frequently trading the same token. We classified these wallets by type (smart contract or EOA) and analyzed their temporal distances, i.e., gaps between recurring appearances. These distances help track consistency in trading patterns.

5.0.1 Temporal Distance Analysis

To understand the recurrence behavior of hyperedges, we calculated the **temporal distance**, defined as the number of days between consecutive occurrences of the same hyperedge.

Example 1 (Two Occurrences):

- **Temporal Distance:** 7 days
(e.g., between January 11 and January 18)

Example 2 (Multiple Occurrences):

- **Temporal Distances:** 3, 5, 1, 1 days
 - 3 days (March 12 → March 15)
 - 5 days (March 15 → March 20)
 - 1 day (March 20 → March 21)
 - 1 day (March 21 → March 22)

This analysis helps reveal how regularly or sporadically hyperedges (tokens) reappear over time.

Temporal Distance Distribution

To analyze recurrence patterns across the network, we plotted histograms of temporal distances.

5.0.2 Node-Level Analysis

Each node’s activity was analyzed by degree (number of tokens traded per day), type (smart/EOA), and frequency of participation. Peaks in node degrees indicated influential wallets or hubs in the network.

5.0.3 Edge-Level Analysis

Edges, representing token transfers between nodes, were studied for frequency, recurrence, and diversity of participating nodes. This provided insights into transfer patterns and direct wallet-to-wallet interactions.

5.0.4 Graph-Level Analysis: s-Adjacency and s-Components

To evaluate the structural properties of our token-user hypergraph, we analyzed *s-adjacency* and *s-components* among hyperedges (tokens). These concepts help uncover underlying patterns of user interaction across NFTs, enabling us to quantify the cohesiveness and fragmentation of the ecosystem.

s-Adjacency

Two hyperedges are said to be **s-adjacent** if they share at least s common nodes (i.e., users). Formally, hyperedges e and f are s -adjacent if $|e \cap f| \geq s$. For example:

- $e = \{A, B, C\}$, $f = \{B, C, D\} \Rightarrow$ 2-adjacent (shared nodes: B and C).

We computed s-adjacency by comparing every pair of tokens occurring on the same day. Sample output includes:

- (53, 69) \rightarrow Shared node: 101933, Count: 1
- (53, 463) \rightarrow Shared nodes: 21017, 91067, Count: 2

This process highlights how tokens are interconnected through overlapping user bases.

s-Components

An **s-component** is defined as a maximal set of hyperedges in which every pair is connected through a sequence of s -adjacent hyperedges, known as an s -*path*. For instance:

- Hyperedges: $A = \{1, 2, 3\}$, $B = \{2, 3, 4\}$, $C = \{3, 4, 5\}$, $D = \{6, 7, 8\}$
- **Component 1 (s=1)**: A, B, C (interconnected via overlapping nodes)
- **Component 2**: D (isolated)

These results demonstrate the varying degrees of token interconnectivity based on the number of shared users.

1. Cross-Project User Overlap When two tokens are s -adjacent (e.g., $s = 2$), the shared users suggest cross-project investment or interest. These overlapping users may serve as collectors or stakeholders in both projects.

Use Case: Detect inter-community interactions for marketing strategies, collaborative airdrops, or fraud pattern detection (e.g., wash trading).

2. Bridging Hyperedges and Influence Zones Certain hyperedges act as bridges between otherwise disconnected communities. Removing such a hyperedge would split a component into smaller ones, making it a central influencer in the network.

Use Case: Identify key tokens critical to community cohesion — useful for influencer detection or resilience studies.

3. Token Similarity via User Base Tokens that share many users are likely to have similar audience interests. By measuring user overlap, one can group tokens with similar communities.

Use Case: Build recommendation systems (e.g., “Users who bought this also bought...”) or cluster similar NFT collections.

4. Market Activity and Virality Detection The emergence of large or highly interconnected s -components on specific days may indicate heightened market activity, virality, or coordinated events. Sudden surges in s -adjacency could point to manipulation or promotional campaigns.

Use Case: Monitor and detect market anomalies, promotional spikes, or influential events through changes in network structure.

5. Temporal Evolution of Components By tracking s -components over time, we can study how the ecosystem grows or contracts:

- Do new tokens merge into existing communities?

- Are certain tokens persistently isolated?

Use Case: Understand ecosystem development, token adoption trends, and long-term community behavior.

Key Metrics Analyzed

From our daily analysis: We applied this analysis to daily hypergraphs. On the day 2018-07-15, we found:

- **S1-component:** 338, 53, 69, 463
- **S2-component:** 520, 484, 494, 519
- **S1-component** (e.g., 338, 53, 69, 463): In this group, token 53 acts as a bridge by sharing common nodes with both 69 and 463. Additionally, tokens 69 and 338 are also connected through a shared node. As all these tokens are interconnected through mutual overlaps, they collectively form a single s-component.
- **S2-component** (e.g., 520, 484, 494, 519): In this case, token 520 shares users with tokens 484, 494, and 519. These mutual connections result in all four tokens forming a single s-component under the $s=2$ adjacency condition.

Number of s-components Indicates the number of distinct token-user communities for a given s .

The size of the largest s-component shows how many tokens are part of the main connected group — meaning these tokens share users and are actively linked within the ecosystem

6 Results

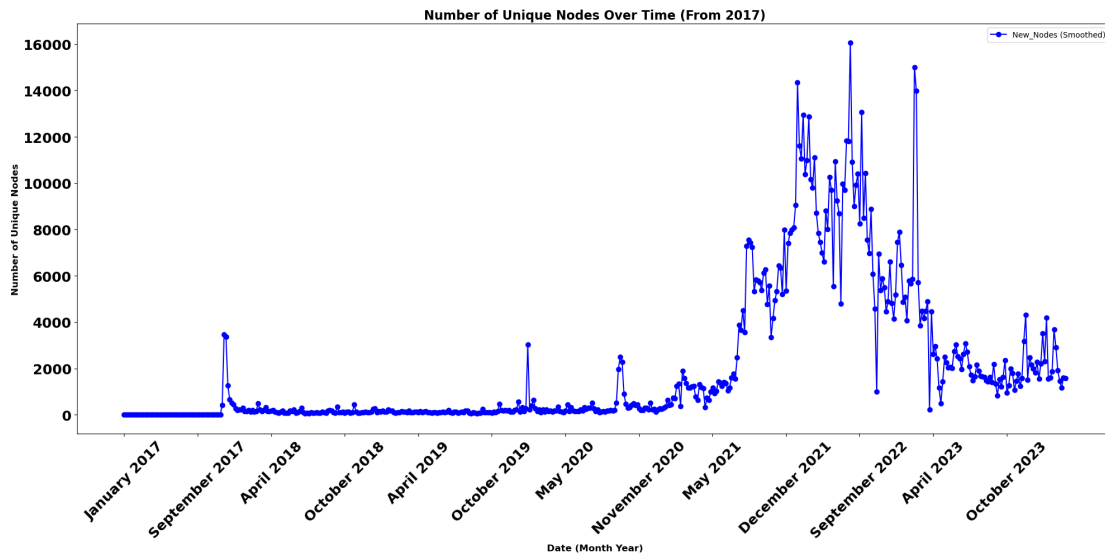


Figure 6.1: The plot illustrates the daily addition of new unique nodes, reflecting the network’s growth of unique wallets over time. Each data point represents the number of wallets engaging in transactions for the first time on that specific day. By examining this plot, we can gauge how quickly the network is growing, spot trends in how new users are joining, and identify times of rapid growth or slowdowns. This information helps us understand how the network is evolving and how its adoption is changing over time.

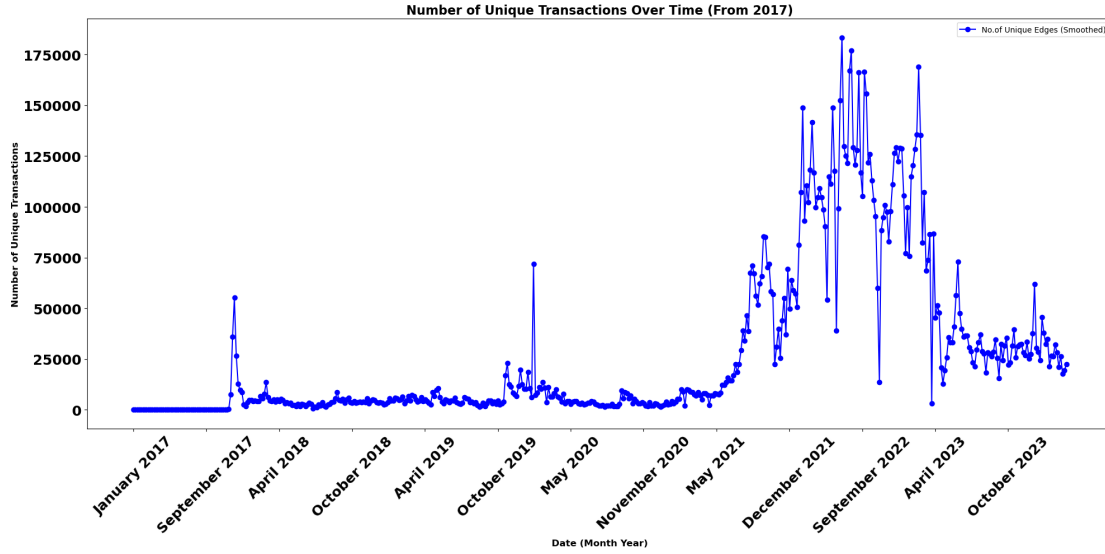


Figure 6.2: The plot depicts the number of new transactions occurring each day, providing valuable insights into transaction activity over time. By analyzing these daily changes, we can observe how transaction volumes vary, such as identifying significant spikes or drops in activity. For instance, a sudden increase in transactions on a specific day may indicate a major event or shift in user behavior. This information is crucial for understanding how the system behaves and helps in making smart decisions based on how transaction patterns change over time.

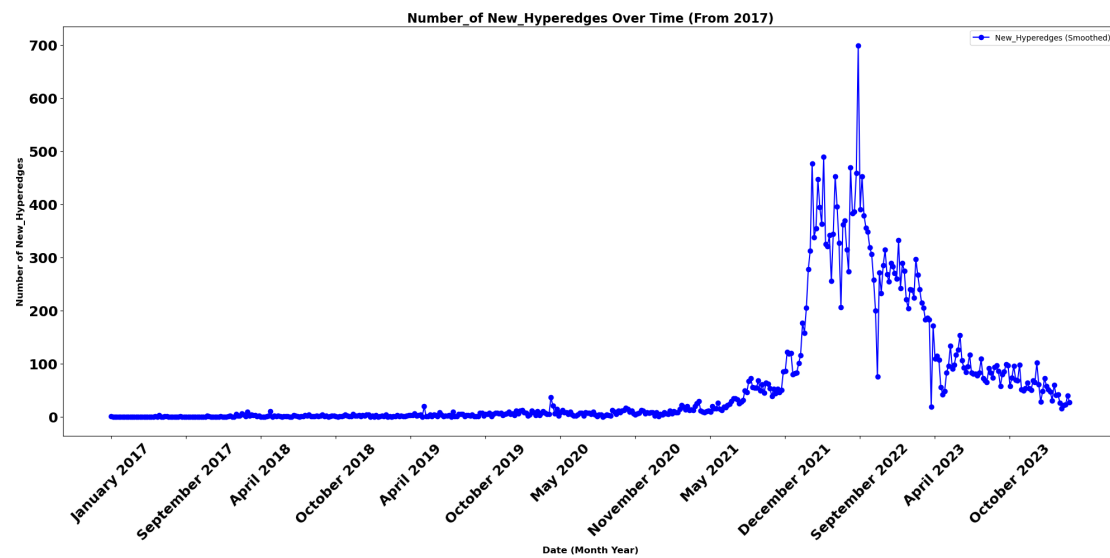


Figure 6.3: By plotting the graph between days and the number of new unique elements being added over time, we can easily track how many new tokens are emerging each day. This visualization helps identify trends in the introduction of new tokens, revealing periods of increased activity or significant events

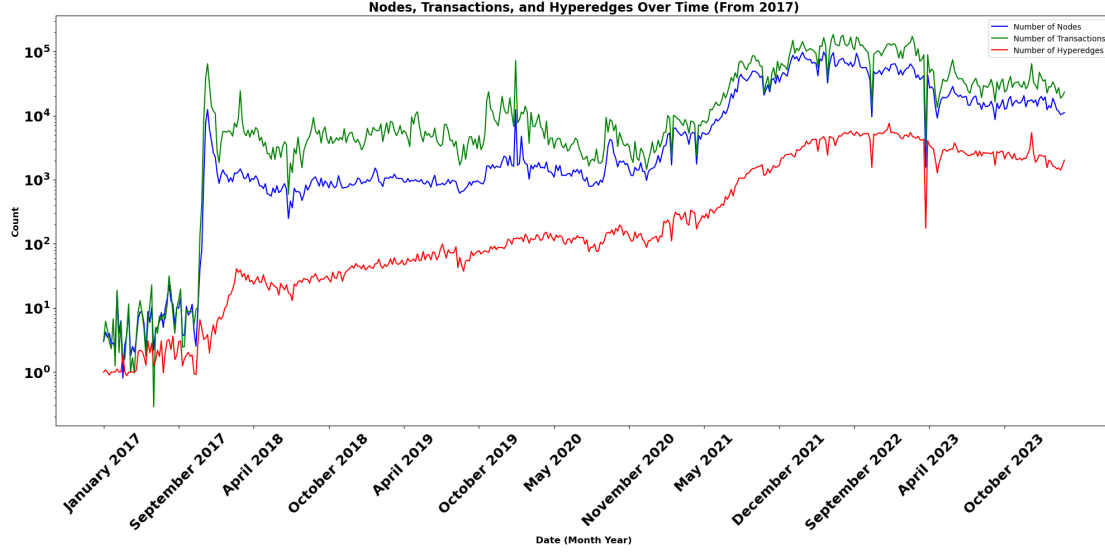


Figure 6.4: The plot tracks the daily changes in the number of active wallets (nodes) involved in transactions, offering a clear view of how network activity fluctuates over time on daily basis. By observing these variations, we can identify trends in user engagement, such as whether the network is expanding or contracting. The plot also helps to detect patterns, revealing consistent increases or decreases in node activity, which provide valuable insights into the overall dynamics and health of the network. The log scale on the y-axis, which enhances the visualization of the plot by compressing large ranges of data, allowing both small and large changes in the number of nodes (wallets) to be observed more clearly. On a normal scale, significant variations might overshadow smaller fluctuations, making it difficult to detect trends or changes in network activity. The log scale, however, evenly spaces out the data, making it easier to see both minor and major shifts in node participation over daily basis. Plotting the graph between days and the number of nodes, transactions and hyperedges(tokens) provides the insights of how the wallets, transactions and tokens are being varied over time . The plot shows the number of transactions (edges) on a daily basis, where each edge connects two nodes. This detailed view allows us to track the volume of transactions occurring each day, offering insights into daily activity levels within the network. By examining these daily transactions, we can gain a clearer picture of how transaction activity evolves over time, identify trends in user interactions, and understand how network engagement changes from day to day. The day vs transactions graph is plotted on a logarithmic scale to better analyze the increase in transactions and reduce any confusion or ambiguity. A logarithmic scale is used to compress large ranges of data, making it easier to visualize both small and large changes in transaction volume. The plot illustrates the relationship between days and the number of tokens, The tokens are represented as hyperedges in this context providing insight into the number of unique tokens being transferred by the nodes each day. Plotting the relationship between days and the number of tokens on a log scale for the y-axis enhances the visualization of data with large variations, making it easier to detect trends, outliers, and exponential growth or decay in token activity. It provides a clearer understanding of token transfer dynamics, highlights periods of significant change, and offers better insights into the distribution and volatility of token transfers over time.

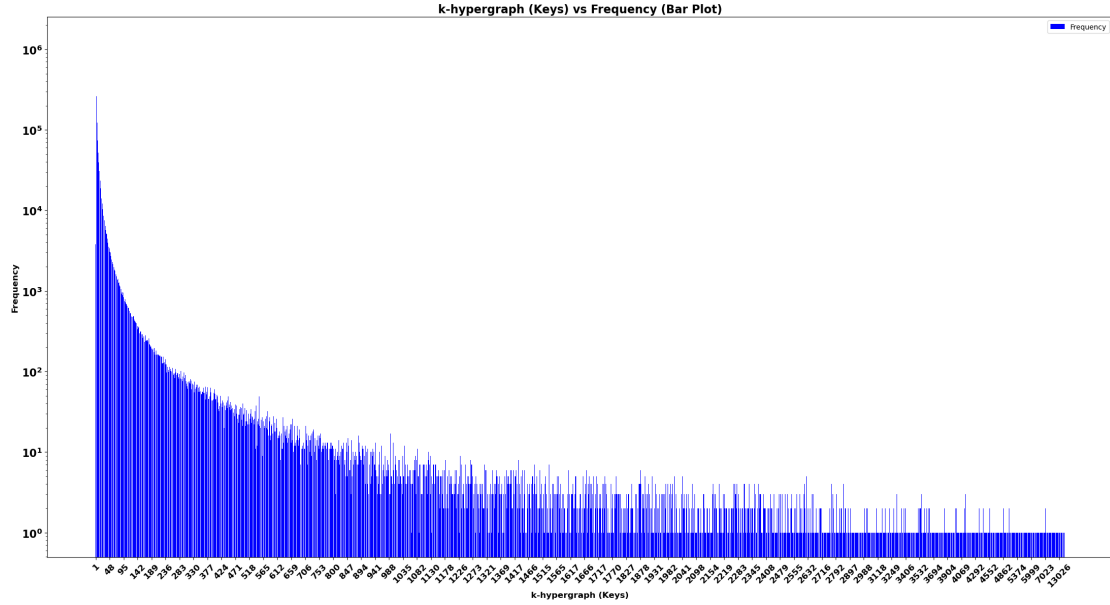


Figure 6.5: The plot shows the frequency distribution of hyperedges of different sizes within the dataset. Each data point represents the count of hyperedges containing a specified number of nodes, where a 1-hyperedge indicates hyperedges with a single node, 2-hyperedges include two nodes, and so forth. This distribution helps to illustrate the overall connectivity represented in the hypergraph

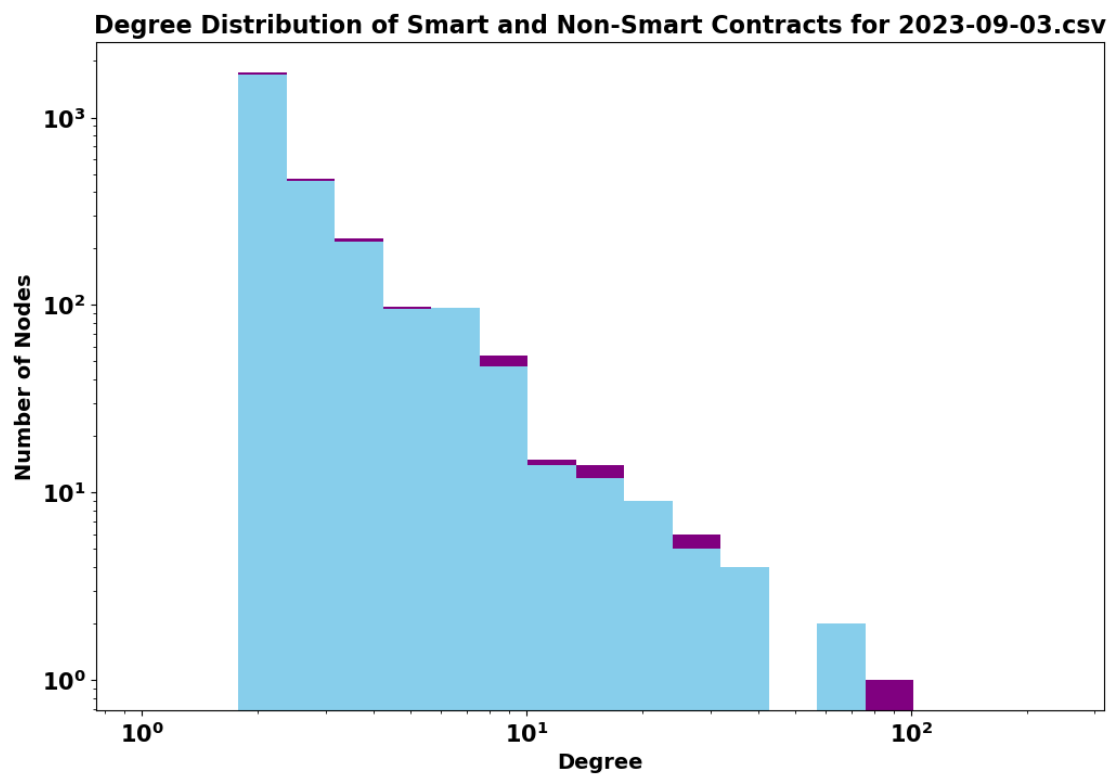


Figure 6.6: Degree of the Node represents the no.of Tokens it is transacting on that particular day. The degree distribution is a probability distribution that shows the frequency of nodes for each degree value. Here the nodes with smart contract is represented in Blue color and the externally owned accounts are represented in sky blue color to differentiate the wallet type that is involved in the transaction of various tokens.

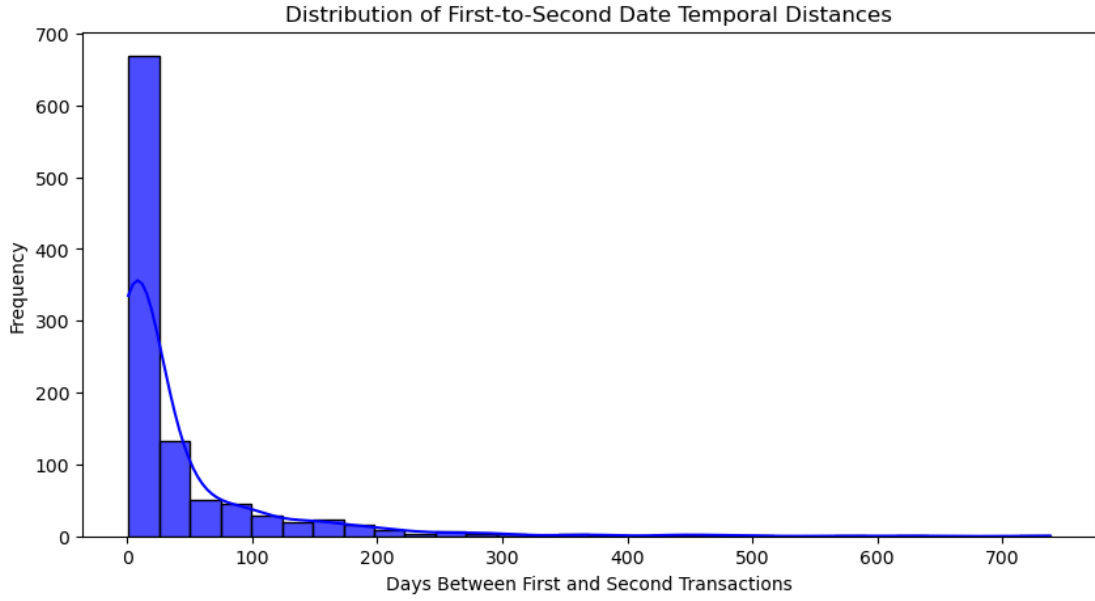


Figure 6.7: First-to-Second Appearance: Temporal distance between the first and second occurrences of each hyperedge. X-axis: Number of days between the first and second appearances of each hyperedge and Y-axis: Frequency (number of hyperedges with that specific time gap), Indicates how quickly hyperedges reappear after their first occurrence. A concentration at smaller values implies frequent or regular transactions and a broader distribution indicates irregular or infrequent activity

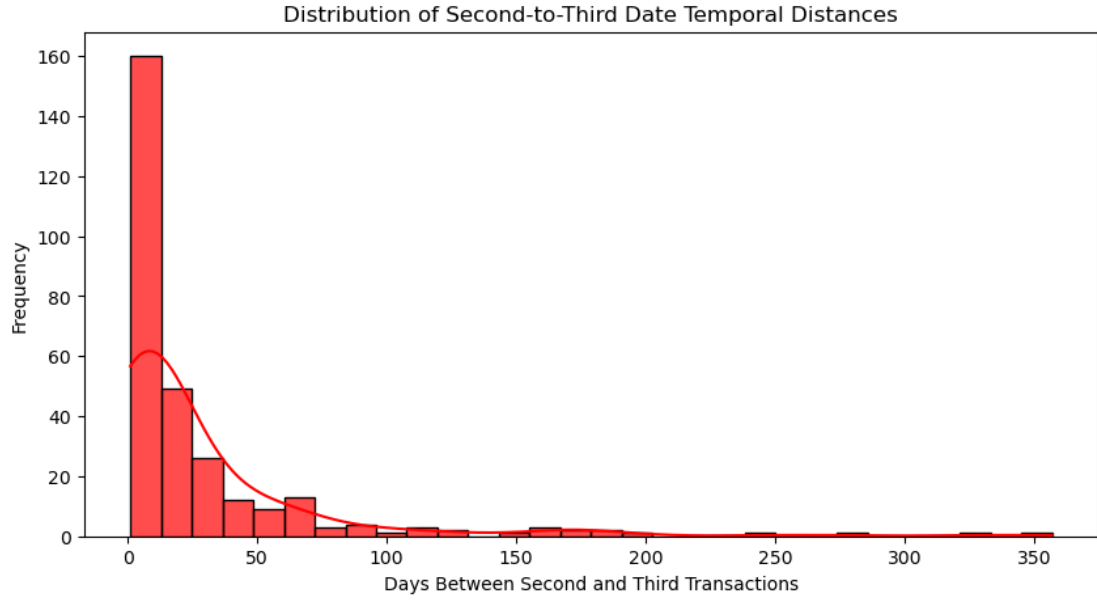


Figure 6.8: Second-to-Third Appearance: Temporal distance between the second and third occurrences of each hyperedge. X-axis: Number of days between the second and third appearances of each hyperedge and Y-axis: Frequency (number of hyperedges with that specific time gap) Indicates whether hyperedges tend to become more frequent after the second transaction A shift toward lower values implies increasing activity Long gaps suggest that some hyperedges remain inactive for extended periods

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