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A network analysis of the non-fungible token (NFT) market: structural characteristics, evolution, and interactions

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Abstract

Non-fungible tokens (NFTs) are a type of digital asset that can prove ownership of both virtual and physical assets using blockchains. Even though creating and trading NFTs have experienced a significant increase, research on the NFT market and its features is limited. In this study, we aim to bridge this gap by conducting a comprehensive analysis on the NFT market and its evolution from a network perspective. We examined the transactions network between NFT buyers and sellers and analyzed the structural characteristics of the NFT trades network. Additionally, we looked at how NFT usage and transactions have changed over time. Our findings indicate that a few participants are responsible for most of the NFT sales and purchases, while the majority of the addresses have only a few NFT transactions. Furthermore, we investigated the structural properties of the NFT trades network, including centrality measures, clustering coefficient, and assortativity, and how they have changed over time. We also explored the interactions between NFTs by constructing a graph of NFT relations. We identified four major communities and highlighted the top NFT projects in each community. We also examined the NFT projects that buyers mostly purchase together.

Keywords: Blockchain, Transaction graph, Complex networks, Non-fungible token

Introduction

Non-fungible tokens (NFTs) have gained significant attention in recent years as a digital asset for various purposes, such as art, collectibles, profile pictures, identity tokens, and real-world asset ownership. NFTs are unique tokens that demonstrate digital asset ownership and are permanently stored on a blockchain like Ethereum, which is one of the most popular blockchains that support NFT creation and trading. It utilizes standard interfaces for representing NFTs: ERC-721[1] and ERC-1155[2], making it easy for developers to create their NFTs.

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[1] https://eips.ethereum.org/EIPS/eip-721.

[2] https://eips.ethereum.org/EIPS/eip-1155.

A wide range of studies has examined Ethereum transactions from various perspectives, attempting to gain insight into them through the quantitative features they offer. These studies have observed the transactions from different viewpoints, such as analyzing the transactions graph and its structural and temporal features (Lischke and Fabian 2016; Di Francesco Maesa et al. 2017; Motamed and Bahrak 2019; Chan and Olmsted 2017; Chen et al. 2018; de Azevedo Sousa et al. 2021), deanonymization of cryptocurrency users based on their transaction history (Béres et al. 2021; Koshy et al. 2014; Ober et al. 2013; Chen et al. 2020), and analysis of cryptocurrency prices (Phillips and Gorse 2017; Stosic et al. 2018; Sun et al. 2020). Still, little work has been done on NFTs and their quantitative features compared to the number of studies available on cryptocurrency transactions and fungible token transfers.

There have been monetary and non-monetary studies on NFT markets. Monetary studies mainly concentrated on the price analysis of NFT projects, the prediction of prices over time, and the price relation between NFTs and other cryptocurrency tokens. On the other hand, non-monetary studies analyze the quantitative features of NFT projects and transactions. We emphasize non-monetary studies more due to their relevance to our research.

From a monetary point of view, Dowling et al. (2022a; b) analyzed the price of Decentraland NFTs, which are tokens identifying virtual land on the Decentraland platform, and studied the relation of Ethereum and Bitcoin cryptocurrency prices with NFT prices. Furthermore, Kapoor et al. (2022) analyzed the influence of social media, such as tweets, on the NFT prices and provided a framework to predict the value of NFT assets based on tweet features.

From a non-monetary view, Nadini et al. (2021) provided the first quantitative analysis of NFTs. In their work, they measured the size of the NFT market and the contribution of each NFT category to the total NFT market size. They showed that the NFT market had experienced significant growth from July 2020, with Art and Gaming categories having the largest market volume and being the most transacted, respectively. Moreover, they analyzed the distribution of different NFT features, such as average price in USD, number of sales per NFT, and number of assets per collection; they claimed that the power law distribution was the best fit for these features. Additionally, they examined the graph of traders and the network of NFT relations and studied the network properties regarding them. They show that NFTs are frequently bought and sold by traders in the same collection. Finally, they created a framework based on NFT visual pictures to predict NFT sales. As a second attempt to analyze NFTs, Ante et al. (2022) emphasized the analysis of NFT subprojects and examined 14 NFT markets and their features. The authors collected the number of sales, the USD amount spent on sales, and the number of unique wallets involved for each Ethereum NFT present in the chosen markets. Ante et al. concluded that NFT markets are interdependent and significantly affect the formation of different NFT markets. They also found that some NFT markets have negative and positive effects on other project sales. Casale-Brunet et al. (2021) concentrated on the graph structure of NFT interactions and their properties. They collected data on the eight most significant NFT projects and formed the transactions graph of the projects. They then examined topological features such as degree distribution, density, clustering coefficient, and assortativity. They report a power law distribution of node degrees based

on the degree distribution data. Vasan et al. (2022) analyzed the NFT artworks and the relation between artists, such as the invitation network of artists. They collected art NFT data from the Foundation platform, including artwork creator, NFT creation time, and bid history. Using the collected data, the authors investigated the timeline of NFT adaptation on the Foundation platform, the effect of Twitter accounts on the value of NFT artworks, and the social network of artists.

In summary, some of the current work on the subject takes a project-based view, analyzing the most dominant existing NFT markets, while others maintain a general perspective examining the general features of NFT transactions and sellers. However, to the authors' knowledge, no work has been done to give a complete view of the current and historical features of NFTs and their transactions while also taking into account NFT projects. This limitation presents a significant problem where NFT creators and traders may not fully understand the relationship between different NFT projects and how the overall NFT community evolves through time. Our work bridges this gap by analyzing the near-complete graph of NFT transfers through time to show how the NFT market has grown. Additionally, we show the interactions between different NFT projects to pinpoint how various NFT submarkets are related and interact with one another.

The rest of the paper is organized as follows: First, "Methods" Section discusses how we collected NFT data for different years, how we created the graph of NFT transfers and NFT interactions, and what features we analyzed. Next, we provide the results of our study in "Results and discussion" Section and interpret our findings. Finally, "Conclusion" Section concludes our study and suggests future research directions.

Methods

This section discusses the methods we used to conduct research into the NFT market. First, "Data collection" Section explains our data collection process. Next, "NFT transfer graph analysis" and "NFT transfer graph" Section 2.4 and 2.5 present the NFT transfer graph and the features we use. Finally, "NFT–NFT graph" and "Community detection" Section and discuss the NFT–NFT graph and its communities, which we used to analyze NFT relations.

Data collection

We collected the NFT transfers from June 2017 until February 2022. The data was obtained using the Moralis platform[3], which offers various APIs for collecting blockchain data. We used the "transfers" API provided by the Moralis platform, which enabled us to obtain Ethereum NFT transfers within a specified date range. The API response provided the following information for an NFT transfer:

- **Token Address:** It shows the address of the NFT contract holding the NFT.
- **Token Id:** It shows the id of the NFT in the contract that, combined with the NFT contract, denotes a unique NFT in the Ethereum blockchain.
- **From Address:** It shows the address that sent the NFT in the transfer.
- **To Address:** It is the address that received the NFT after this transfer.

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[3] https://moralis.io.

Table 1 Summary of the collected NFT transfers

Year	2017	2018	2019	2020	2021	2022
Average monthly NFT transfers	112,503	247,350	1,655,634	509,856	2,481,599	8,814,212
Total NFT transfers	1,350,046	2,968,202	19,867,610	6,118,272	29,779,198	17,628,425
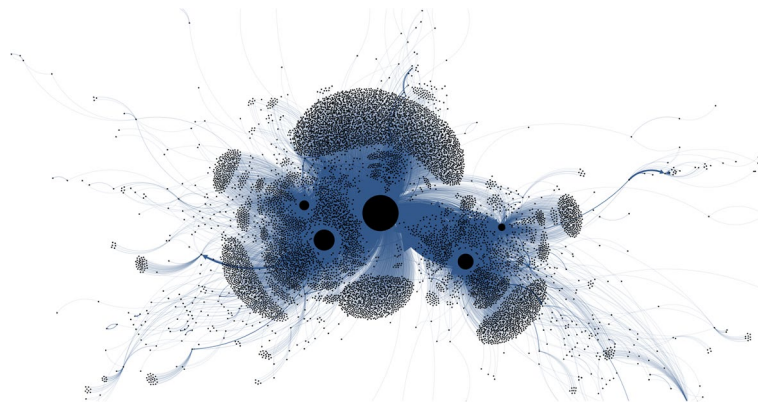
Fig. 1 A sample of the NFT transfer graph. The nodes in this graph represent the Ethereum addresses with at least one NFT transaction. The edges in the graph show the NFT trades between two addresses. The sample shows all the NFT transfers in November 2017. The largest node in the graph represents the zero address in the Ethereum network, where NFT creations happen from

- **Value:** The amount of money in ETH that was sent in the transfer.
- **Amount:** The number of tokens that were transferred.
- **Contract Type:** It's the type of the NFT contract, which can be ERC-721 or ERC-1155.
- **Block Number:** It shows the block number that stored this NFT transfer.
- **Block Timestamp:** The time that the block was generated.
- **Transaction Hash:** The hash of the transaction that transfers this NFT.
- **Operator:** The address authorized by the NFT owner to transfer the NFT in transactions. It is just present in the ERC1155 contract type.

We stored the 77,711,753 collected transfers in MongoDB[4] due to its fast write performance. Table 1 shows the average number of monthly transactions and the total number of transactions for each year.

NFT transfer graph

After collecting the NFT transfers for the aforementioned years, we created an NFT transfer graph for our analysis. The graph shows the interaction of addresses regarding NFT sales and purchases. The nodes and edges in this graph represent the Ethereum addresses and NFT transfers, respectively. Each address has a unique identifier, and each NFT is uniquely identified by combining its token address and token ID. The edges,

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[4] https://www.mongodb.com.

Table 2 Summary of the NFT transfer graph features

Feature name	Overview
In-degree and out-degree distribution	The distribution of incoming and outgoing NFT transfers.
Average node assortativity through time	It shows how much nodes prefer to connect with similar nodes.
Average clustering coefficient through time	It shows the clustering effects in the NFT transfer graph over time.
Node centrality distribution	Closeness, degree, and PageRank centrality distributions.
Average NFT token per address through time	How many NFTs each node holds on average over time.
Number of transactions through time	The total number of NFT transfers over time.
Total transaction volume in ETH/USD through time	The total aggregated value of all transactions over time.

which are the NFT transfers, also include the value of the transfer in ETH, the number of NFTs transferred, and the transaction number. Figure 1 depicts a sample of the NFT transfer graph.

Algorithm running methods

To analyze the NFT transfer graph discussed in "NFT transfer graph analysis" Section, we employed three approaches: Neo4j[5], Python's NetworkX[6] package, and calculation of the metrics from the raw files. All the calculations are performed on a server with eight processing cores and 64 Gigabytes of RAM. Neo4j is a graph database designed for storing graph nodes and edges. It provides tools for querying the underlying graph data and analysis of the stored graph. For running the chosen algorithms on the NFT transfer graph, we used the Neo4j Graph Data Science (GDS) library[7]. The library consists of various graph algorithms and other tools for graph analysis. Additionally, we used NetworkX, a Python package designed for interaction with complex networks, to examine the NFT transfer graph structure over time. Moreover, in some instances, it was unnecessary to create the complete graph, which would incur a high resource cost. Instead, we used Python to read the raw transfer files from the disk and calculate the metrics, resulting in much faster analyses.

We used different approaches since not all of our needed algorithms were available in a single method, and we were limited by the space and time complexity of some of the algorithms. Furthermore, it should be noted that our NFT transfers graph data was around 32 Gigabytes, so there is a limit on storing all the data in RAM for the analysis. Considering the mentioned points, we used the best tool from the three approaches for each algorithm.

NFT transfer graph analysis

In this section, we discuss the features used in our analysis and the algorithm used for each. We classify the features as network characteristics and transaction features, which we introduce in the following sections. Table 2 gives an overview of all features used for analyzing the NFT transfer graph.

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[5] https://neo4j.com.

[6] https://networkx.org.

[7] https://neo4j.com/docs/graph-data-science.

NFT transfer graph

Network characteristics

From the network perspective, we analyzed features related to node degrees, assortativity, clustering coefficient, and centrality measures. The calculated features are explained in detail below. For each feature, we explain what it shows and how we calculated it.

In-Degree and Out-Degree Distribution It shows the distribution of incoming and outgoing edges, NFT transfers, in the NFT transfer graph. It shows how many of each degree exists in the graph, which indicates how many NFTs each address sales or purchases in the graph. In-degree and out-degree distributions are essential for analyzing the overall network structure of the graph. For calculating in-degree and out-degree, we used a Neo4j query to calculate the number of incoming and outgoing connections for each node in the graph. Then, we used this data to calculate in-degree and out-degree counts in the graph.

Average Node Assortativity through Time Assortativity is a metric that shows how much nodes prefer to connect with similar nodes. We used node degree as the similarity metric in this study. An assortativity near 1 indicates a positive tendency of addresses to connect with addresses with a similar degree. On the other hand, an assortativity near −1 means a tendency to connect with different nodes. We calculated the average assortativity for each month to analyze the effect over time. For calculating this feature, we used the NetworkX Python library to load the graph for each month and calculate the average assortativity.

Average Clustering Coefficient through Time The clustering coefficient shows how neighbors of a given node are connected to each other. It is calculated as the number of edges between the neighbors of a given node to the maximum number of possible edges. A clustering coefficient of 1 means a high clustering effect between node neighbors, while a 0 indicates no clustering effect. We calculated the average clustering coefficient between all nodes for each month to track clustering effects in the NFT graph. Like the average assortativity metric, we used the NetworkX Python package to calculate the average clustering coefficient.

Node Centrality Distribution Centrality is an important network feature that shows the importance of a given node in a graph. There are various types of centralities to calculate node importance in a graph; we use closeness, degree, and PageRank centrality in our study of the NFT transfer graph. We did not incorporate betweenness centrality due to algorithm complexity and long run time. We used Neo4j's GDS library to calculate centrality metrics distribution. The centrality distribution gives insight into the graph structure and how addresses transfer NFTs together.

Closeness Centrality It is calculated as the inverse average of the node's shortest path with other nodes in the graph. In other words, it shows how close a node is to other nodes in the network. A high closeness centrality indicates a short path to other nodes in the graph and being central to the graph structure.

Degree Centrality It is calculated as the number of a given node's incoming and outgoing links. A high degree centrality means that the node has more connections in the network, so it's more important in the network structure.

PageRank Centrality It is calculated as the probability of reaching a given node by starting from a random node in the graph (Brin and Page 1998). It considers nodes that other nodes reach with a higher probability more important.

Transaction features

Average NFT Token per Address through Time It shows the number of NFTs each node holds on average over time. It shows how NFTs are distributed between addresses. It can provide insights about NFT ownership patterns in the graph through time.

Number of Transactions through Time This metric shows how the total number of NFT transfers changes over time. It can help in understanding the activity level in the NFT graph and how popular NFTs are in a period.

Total Transaction Volume in ETH/USD through Time It shows the total aggregated value of all transactions over time. It indicates the overall economic activity in the NFT market and its changes over time.

NFT–NFT graph

In this section, we describe the process of creating an NFT–NFT graph to analyze relations between NFTs. The NFT transfers graph we described in "NFT transfer graph" Section helps analyze how addresses interact with each other for buying or selling NFTs. On the other hand, the NFT–NFT graph is useful for finding the relations between the NFT projects.

Bipartite NFT-address graph

The first step to creating the NFT–NFT graph was to form a bipartite graph of the relationship between addresses and NFTs. The bipartite graph is defined as below:

- **Nodes:** The nodes can be addresses or NFTs in the final bipartite graph.
- **Edges:** An edge in the bipartite graph can be between an address and an NFT. Let's assume that address A has an edge to NFT N. This relationship shows that N has been bought by A at least once in our dataset.

To create the bipartite graph, we simply iterated over all collected NFT transactions, and for each transfer, we created an edge connecting the address to the NFT. As mentioned before, each NFT is uniquely identified by concatenating the Token Address and Token Id.

Bipartite graph size reduction

Before creating the NFT–NFT graph from the bipartite graph, we applied some changes to the bipartite graph to make it more meaningful and reduce its size for further analyses. The changes are described below:

NFT Aggregation In our research, we made a significant observation that led us to modify our approach for community detection and its analysis. We realized that including all unique NFTs in our graph was unnecessary for achieving meaningful results. Based on this insight, we changed our definition of nodes in the graph, which resulted in a more meaningful analysis and a significant reduction in the final graph's size.

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To achieve this, we redefined the nodes based on the Token Address, as opposed to concatenating the Token Address and Token ID. It is important to note that the Token Address represents the NFT project contract. The rationale behind this decision stems from the fact that NFT projects inherently represent a collective of NFTs within a specific ecosystem. Analyzing the relationships and interactions between NFT projects allowed us to gain deeper insights into the dynamics and communities within the NFT space. By leveraging NFT projects as the nodes in our graph, we could identify and explore meaningful connections and patterns that exist at a higher level of abstraction that shows the relationships between different NFT types instead of the relationships between individual NFTs.

Zero Degree Nodes Removal Before creating the NFT–NFT graph, we removed the nodes that would be isolated in the NFT–NFT graph. To achieve this, we removed every NFT node with no address node forming an edge with this NFT node and any other NFT node. According to our definition of the NFT–NFT graph, discussed in "NFT–NFT graph creation" Section, edges are formed between a set of NFT nodes when an address has edges to all nodes in the set. In other words, NFT nodes connect in case an address buys them at some time during all collected NFT transfers. Therefore, without any address with the mentioned features, the NFT node would be isolated in the final NFT–NFT graph, and we can safely remove it.

NFT–NFT graph creation

After creating the bipartite graph of addresses and NFTs and applying the size reduction steps, we created the NFT–NFT graph. The condition for creating edges between a set of NFTs is being connected to a single address node in the reduced bipartite graph. For example, If address node A is connected to NFT nodes $N1$, $N2$, and $N3$ in the bipartite graph, the nodes $N1$, $N2$, and $N3$ will be connected in the NFT–NFT graph. We used Spark (Zaharia et al. 2016) to find the NFT projects with the same owner and connected those NFT projects. Spark was a good choice due to its fast in-memory computation using resilient distributed datasets (RDDs).

Community detection

Community detection is significant to our study of the relationship between NFT projects since it allows us to observe the groups in the NFT–NFT graph and their relations.

We experimented with two algorithms for community detection on the NFT–NFT graph: Traag et al. (2018) and Blondel et al. (2008). Both algorithms try to separate the communities of nodes to maximize modularity. Modularity is a metric for determining how densely nodes are connected in their assigned community. Therefore, a higher modularity score denotes a higher density in each community group. The Louvain algorithm is a heuristic method for community optimization (Blondel et al. 2008). The Leiden algorithm was introduced later and fixed some of the problems with the Louvain algorithm. In some cases, The Louvain algorithm can lead to poorly connected or disconnected communities (Traag et al. 2018). The Leiden algorithm improves this and guarantees connectivity inside communities. Moreover, The Leiden algorithm performs better due to the fast local move approach (Traag et al. 2018).

We ran the community detection using both algorithms and calculated the modularity and the run time. The run time was significantly better using the Leiden algorithm, similar to their statement of performance improvement over Louvain. Also, regarding modularity, both algorithms were similar, and little difference was observed. Therefore, we chose the Leiden algorithm for the community detection of the NFT–NFT graph due to its better performance on our graph, which has many nodes and edges.

Results and discussion

We present our results in this section and interpret and explain our findings. First, we provide the results of the features mentioned in "NFT transfer graph analysis" Section. Next, we provide our NFT–NFT graph results, which includes the communities we found in the graph, their relationships, the top NFT projects in each community, and the relationship between NFT projects in the NFT–NFT graph.

NFT transfers graph analysis

This section provides the results of the features we calculated for the NFT transfer graph. We further interpret these features and discuss what they reveal about NFT transfers. First, we present the network characteristics results and discuss the overall structure of the NFT transfer graph. Then, we provide transaction features and our findings.

Network characteristics

Figure 2 shows the in-degree and out-degree CDF distributions. About half of the nodes in the NFT transfer graph have an in-degree of one. On the other hand, the out-degree distribution shows that around 80 percent of the nodes have an out-degree of one. This indicates an 80–20 effect, where a small percentage of nodes are responsible for the majority of transfers. This finding is consistent with a possible power law distribution, where a few hubs have many connections, while most nodes have only a few. Most users in the NFT market are buying a small number of NFTs, while a few users are responsible for the majority of purchases. Furthermore, we analyzed the top 10 users with the highest degree in the graph and found that these nodes consist of both NFT buyers and NFT creators, showing a variety of top actors in the NFT market. The in-degree distribution has a weaker 80–20 effect, but still, around 80 percent
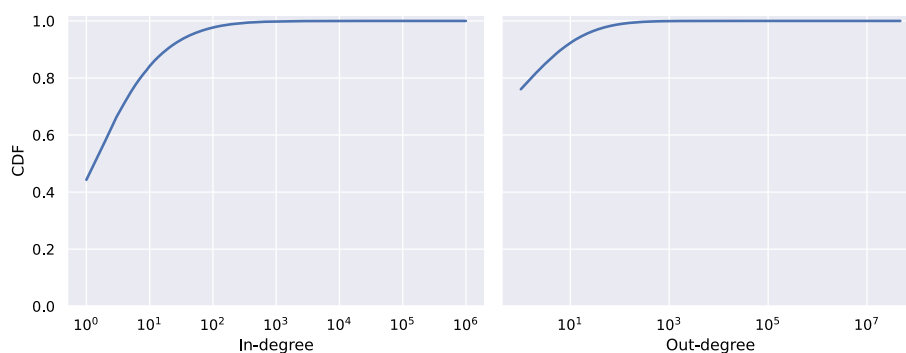

Fig. 2 Degree distribution in the NFT transfer graph. The plot shows the in-degree and out-degree cumulative distribution functions (CDF) for the NFT transfer graph. The plot shows that a large number of nodes have a low degree while few nodes do most of the trades

of the nodes have an in-degree between 1 and 10. Overall, the results suggest that the NFT transfer graph has a structure where a few nodes have many connections while most nodes have low degrees.

Figure 3 depicts the average node assortativity and average clustering coefficient through time for the NFT transfer graph. The average node assortativity through time initially shows a positive trend in the first year, but then it starts to become negative and remains the same. This indicates a mixing pattern where different nodes connect to each other, and the graph shows a disassortative mixing pattern since the assortativity is negative most of the time. This pattern shows that not just hubs sell to each other, and different nodes do transfers.

The rise and fall in assortativity in the first year might be because after NFTs gained more popularity, the actors in the NFT market became more diverse, creating a disassortative mixing pattern in the graph. This pattern suggests that buyers and sellers in the NFT market are not just interacting with others who have similar characteristics, but rather there is a mix of nodes with different characteristics involved in the market.
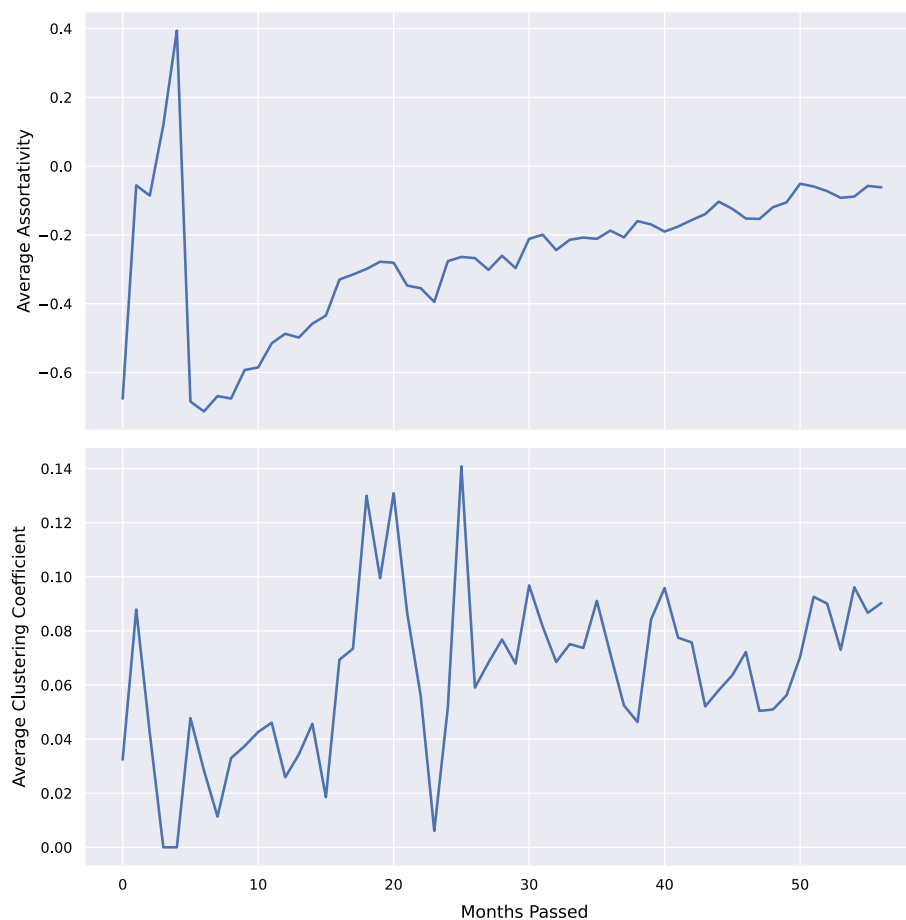
Fig. 3 Average assortativity and clustering coefficient through time. The plot demonstrates a disassortative mixing pattern in the NFT transfer graph, suggesting that buyers and sellers in the NFT market are not just interacting with others who have similar characteristics. A massive decline in the clustering coefficient in November 2019 was observed, which was attributed to the creation of a huge number of NFTs during that period, mostly by Project CryptoKitties, one of the first peaks in NFT adoption and creation
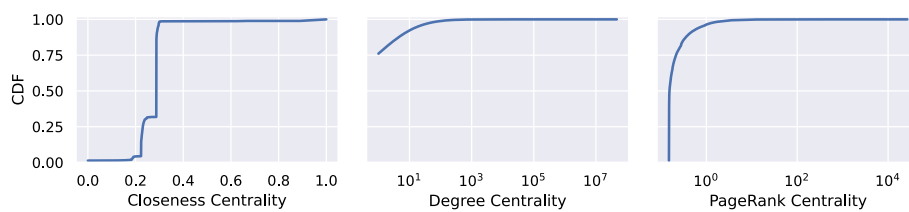
Fig. 4 Centrality CDF through time. The centrality measures show that most nodes have a low centrality while a few are central to the graph structure

The average clustering coefficient through time, on the other hand, exhibits a weak clustering tendency as it is near zero. This might indicate a sparse network where not all nodes are connected. Although it changed over time, the positivity was not significant, and the clustering tendency was low overall. This suggests that there might not be many small groups of nodes with dense connections in the NFT transfer graph.

A noteworthy observation in the average clustering coefficient plot is a massive decline in the November of 2019. A manual analysis of the data collected for this period was performed to understand the underlying cause of this effect. We found out that 97.86% of transactions in this month were from the special Null address in the Ethereum blockchain, where NFTs get created from. From 11th to 17th November 2019, a huge number of NFTs were created that made the graph sparse and reduced the average clustering coefficient. Project CryptoKitties, the world's first blockchain game, had the largest number of NFT creations in the mentioned period and was one of the first peaks in NFT adoption and creation.

Figure 4 shows the results of three centrality measures: closeness, degree, and PageRank. In terms of closeness centrality, the plot reveals that a majority of the nodes possess a low value for this metric. This suggests that there is a high path distance between the nodes, and the graph is not really central as most nodes exhibit a relatively low closeness centrality. With respect to the degree centrality, it is apparent that the majority of nodes have low values for this metric, while only a few nodes exhibit high degree centrality. This is consistent with the degree distribution plot and suggests that the NFT transfer graph has a structure where only a few nodes are highly connected nodes, while most nodes have sparse connections. In other words, the majority of NFT transfers are concentrated in a small number of highly active nodes, while the rest of the nodes have fewer connections. This indicates that a small percentage of participants account for a significant proportion of NFT transactions, highlighting the importance of key players in the market. Additionally, the PageRank measure illustrates that there are a small number of highly influential nodes, while most of the nodes have low PageRank scores. This implies that the NFT transfer graph has a structure where a few highly influential nodes play a critical role in maintaining the overall connectivity of the network.

Transaction features

Figure 5 depicts the number of transactions and the average NFT token per address through time. The plot shows that the number of transactions was mostly low until 2022 when the NFT market experienced a significant surge in trading. Notably, in November 2019, there was a massive spike in the number of transactions due to a large number
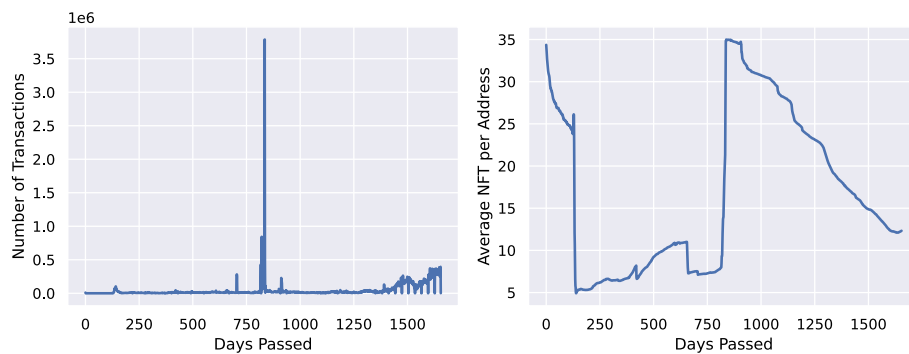
Fig. 5 Number of transactions and average NFT per address through time The plot indicates that the NFT market witnessed a remarkable surge in trading in 2022, and in November 2019, there was a massive spike in the number of transactions due to a large number of NFT creations from the CryptoKitties project. The average NFT token per address increased significantly in November of 2019, but after that, it started to decline as the market became accessible to a broader range of participants

of NFT creations during that period from the CryptoKitties project. The average NFT token per address through time plot shows that the average number of NFT tokens per address increased substantially in November of 2019 due to the creation of CryptoKitties NFTs. However, after November 2019, the average number of NFT tokens per address started to decline as more participants were attracted to the NFT market, resulting in a larger number of addresses with smaller holdings. These results suggest that the NFT market has experienced significant growth in recent years, with the trade of NFTs becoming more popular. The spike in the number of transactions in November of 2019 highlights the significant impact that the introduction of new NFT projects can have on the market. Moreover, the decline in the average number of NFT tokens per address after November 2019 underscores the market's increasing accessibility to a broader range of participants with various financial capabilities.

Figure 6 displays the USD/ETH price and the total transaction value in ETH and USD through time. One notable trend is the alignment between the growth of the NFT market and the ETH price: as the ETH price rises, the total transaction value in USD also increases. Moreover, as the number of trades has recently increased, there is a greater total value of transactions, and this growth is also reflected in the price. The Pearson coefficient between the ETH/USD price value and the total transaction value in ETH is 0.66, and the value is 0.74 for the total transaction value in USD, indicating a positive correlation in both cases.

Observing the plot, it can be seen that the major changes in the USD/ETH price do not affect the NFT market immediately and there is a delay for the effects to be shown in the NFT market. Analytically testing this observation, we found that the correlation of the ETH/USD price value with the total transaction value in ETH increased to 0.70 when shifting the total transaction value 20 days. This delay suggests that the effects of changes in the USD/ETH value may not be immediately observed in the NFT market. Market actors should take this into consideration, understanding that there might be a lag in the propagation of effects from the cryptocurrency market to the NFT market.

These findings have important implications for market players. Firstly, investors and collectors in the NFT market should closely monitor the performance of the
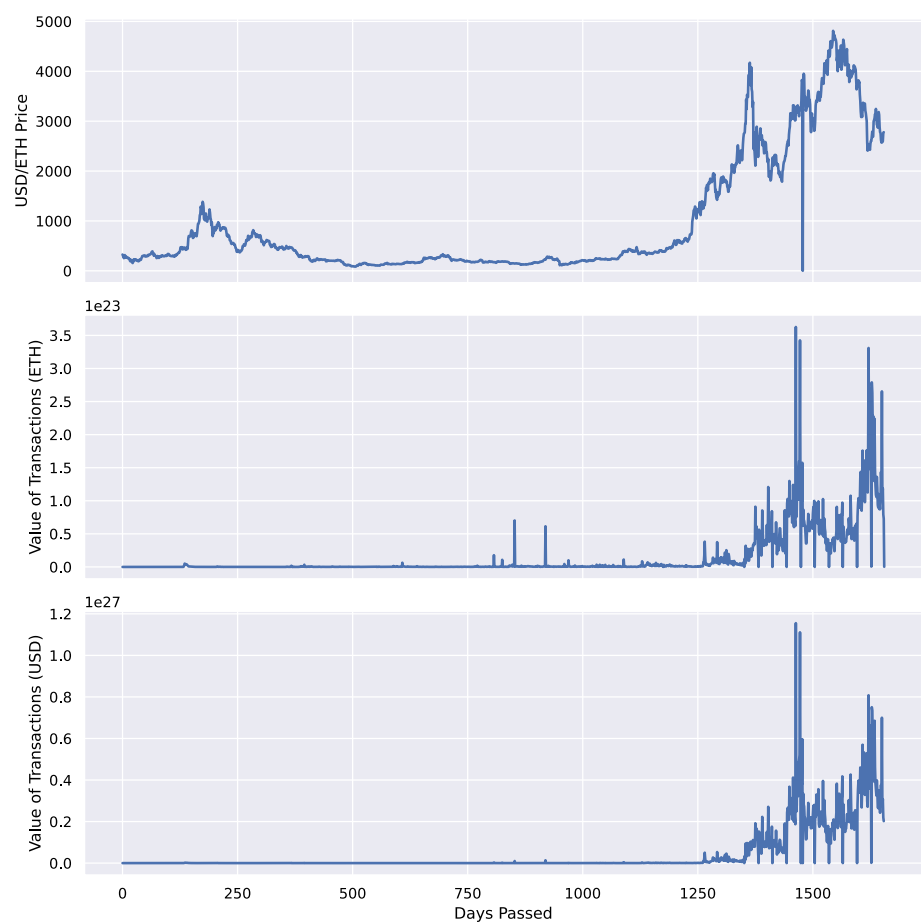
Fig. 6 Value of transactions in USD and ETH. The plot shows that the performance of the Ethereum market highly influences the NFT market

cryptocurrency market, particularly the ETH price, as it serves as a significant driver of the NFT market's growth. Understanding the correlation and delayed effects can help inform investment strategies and decision-making processes. Secondly, market participants may need to allow for sufficient time to pass for the effects in the cryptocurrency market to fully manifest in the NFT market. Rapid reactions based on short-term fluctuations may not accurately capture the overall trend and potential opportunities. As the cryptocurrency market evolves, it is expected that the growth of the NFT market will continue to follow suit, possibly with a certain time lag.

Table 3 Summary of the edges inside and between NFT and NFT graph communities

Community	Edge count	Total edge weight
Orange	421,346	10,812,781,583
Purple	10,740	3,848,307,370
Yellow	363,396	186,495,754,223
Orange–Purple	1974	100,700,830
Orange–Yellow	69,875	3,400,536,920
Purple–Yellow	56,618	9,427,246,668

NFT–NFT graph

As discussed in "NFT–NFT graph" Section, an NFT–NFT graph was created to analyze the relationship between NFT projects. Figure 7 depicts the community detection results after applying the Leiden algorithm. We found four major communities, which are represented using the colors orange, purple, yellow, and black. Table 4 indicates the number of NFT projects in each community alongside their proportion. The orange community is the largest community containing more than half of all NFTs, while the black community only consists of a few NFT projects.

Table 3 displays the number of edges within and between the top three communities to provide insight into the relationship between different communities. As expected, the majority of edges exist within each community, since the community detection algorithm tries to maximize modularity. Interestingly, the yellow community has a much higher density than the orange community (almost 24 times higher). It shows that the yellow community is much denser in its relationships and closer to a complete graph.

Fig. 7 NFT–NFT graph with communities. The graph shows four major communities with the colors orange, purple, yellow, and black. Table 3 provides a summary of the edges within and between these communities, while Table 4 presents the number of nodes in each community. Furthermore, Tables 5, 6 and 7 highlight the NFT projects with the highest degree in the graph, serving as the top nodes within each community. Additionally, Table 8 shows the edges with the highest weight in the network, indicating the frequency at which connected nodes were purchased together

Table 4 Summary of the communities in the NFT–NFT graph

Community	Node count	Proportion (%)
Orange	18,952	57.80
Purple	9972	30.41
Yellow	3598	10.97
Black	266	0.81

We present the top ten most important NFT projects for each community in Tables 5, 6 and 7. The importance of a project is determined by its degree centrality.

Table 5 shows that the orange community's primary focus is on gaming and digital art collections. The top project in this community is the OpenSea Shared Storefront, which provides a platform for various collections. Other popular projects include game-related items such as ASM AIFA All Stars Box Set, Gods Unchained Cards, and Wizards

Table 5 Top NFT projects with the highest degree centrality in the orange community

Rank	Name	What
1	OpenSea shared storefront	Various collections
2	ASM AIFA all stars box set	Football game characters collection
3	Anonymice	Art mice collection
4	Gods unchained cards	Game
5	Cats	Art cat collection
6	Bamboozlers	Art panda collection
7	Wizards & Dragons game	Game
8	The fungible open editions by Pak	Digital art collection
9	FloydsWorld	Access token to Floyd Mayweather's community
10	ArtAI	AI-generated paintings

Table 6 Top NFT projects with the highest degree centrality in the purple community

Rank	Name	What
1	Foundation	Various collections
2	WHO WE ARE 200	Photographs
3	The girls of armament	Avatar collection
4	Universe compendium	Character card collection
5	EMPRESSISTERS	Character card collection
6	ROMA	Photographs
7	FRACTALS	Art collection
8	Eons	Art collection
9	Digitization	Art collection
10	FrameD	Frame collection

Table 7 Top NFT projects with the highest degree centrality in the yellow community

Rank	Name	What
1	Ethereum name service	Decentralised naming
2	WAR token	Game
3	Rarible	Various collections
4	Merge. by Pak	Art/game
5	Enjin	Various collections
6	KnightStory item	Game
7	CryptoAssaultUnit	Assault unit objects
8	Mega crypto polis resource	Game
9	Creepz ShapeShifter	Famous people art cards
10	Rarible	Various collections

Table 8 Top NFT projects bought together

Project	Project	Times bought together
Ethereum name service	WAR Token	3,503,945,553
Ethereum name service	Rarible	2,684,086,928
Ethereum name service	Merge.	2,364,028,271
Ethereum name service	Enjin	2,222,526,499
Ethereum name service	KnightStory item	2,162,018,872
Ethereum name service	CryptoAssaultUnit	1,799,282,678
Rarible	WAR token	1,651,365,217
Ethereum name service	MCP resource	1,574,538,657
Merge. by Pak	WAR token	1,455,432,020
WAR Token	Enjin	1,368,158,169

& Dragons Game. Moreover, the community appears to have a particular affinity for art collections featuring animals, such as Anonymice and Cats.

Table 6 shows that the purple community is more interested in photography, art collections, and avatar collections. The top project in this community is Foundation, which provides a platform for various art collections. The community also shows a strong interest in avatar collections such as The Girls of Armament and character card collections such as Universe Compendium and EMPRESSISTERS.

Table 7 indicates that the yellow community is primarily interested in gaming and various art collections. The top project in this community is the Ethereum Name Service, which provides a decentralized naming service. Other popular projects in this community include game-related items such as WAR Token and KnightStory Item. Moreover, the community shows a significant interest in various art collections, such as merge. by Pak and Creepz ShapeShifter.

Finally, we present Table 8, which shows the top NFT projects that are bought together the most. Ethereum Name Service appears to be the most common project, indicating its high importance in the NFT ecosystem. The table also shows that WAR Token, Rarible, merge. by Pak, Enjin, and KnightStory Item are frequently bought together, indicating that there might be some form of association between these projects. Our community detection results also confirm this relationship since the projects that are mostly bought together are in the yellow community.

Conclusion

In conclusion, our study presents a thorough analysis of the Non-Fungible Token (NFT) market and its characteristics. Our research findings show that the NFT market has experienced a significant spike in creating and trading NFTs, but only a few participants do most of the sales and buys, while most of the addresses have few NFT transactions. We also found that the structural properties of the NFT transfer graph, including centrality measures, clustering coefficient, and assortativity, changed over time, indicating a complex evolutionary pattern in the NFT market. Additionally, we explored NFT interactions which led to the identification of four major communities. By examining the top NFT projects in each community and the NFT projects that buyers frequently purchase together, we provide insights into the preferences of NFT buyers. In summary, our study

bridges a gap in NFT market research and provides valuable insights into the behavior and characteristics of NFT traders from various perspectives. We believe that these findings can benefit investors, traders, and developers in the NFT market. For future work, the following would be beneficial in understanding the NFT market and its relations better:

- The influence of the Twitter NFT community on the NFT market and its analysis will offer valuable insights.
- A study of the NFT market from an economic point of view focusing on wash trading, ROI enhancement techniques, anomalies, and trading strategies will be useful to market participants.
- Adopting a more macro approach, such as utilizing complex systems, can assist market participants and researchers in gaining a deeper understanding of the NFT market.

Declarations

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