Heavy-tailed DecentraPunks - Exploring the Structure of NFT Sales Networks

Nargess Tahmasbi
Pennsylvania State University
nvt5061@psu.edu

Alexander Fuchsberger
Bucknell University
af033@bucknell.edu

Abstract

Non-fungible Tokens (NFT) have received increased attention since 2021. The availability of the vast amount of public sales transaction data has created an unprecedented opportunity that calls for research to uncover the underlying mechanism in which NFT networks evolve. Our main goal is to understand the new space of NFT-based crypto art exchange and the structure of the trading network. We use data from the Crypto Punks collection and perform a data-driven quantitative study based on real-time trading and sales data to carry out a two-folded methodological approach that is first applied to this domain. We borrow the citation analysis and social network analysis from bibliometrics and the social network domain and apply them to the NFT space to explore the trading network structure. We found that despite being based on unique and non-interchangeable tokens, the NFT-based CryptoPunks transactions network follows the scale-free network structure, the similar pattern that is observed in Web 2.0 social networks and cryptocurrency transaction networks, where a few actors have dominant centrality. Our study demonstrates the applicability of the two approaches from bibliometrics and social network analysis to the context of unique digital assets trading.

Keywords: Crypto art, non-fungible tokens (NFT), Digital Assets, Blockchain, social network analysis, bibliometric analysis

1. Introduction

Non-fungible Tokens (NFT) are tokens that are based on blockchain technology (Fairfield, 2021). An NFT is a unique unit of data, called a digital asset, that is stored on blockchain. Its digital certificate of ownership is offered through smart contracts of Ethereum (Wang et al., 2021). NFTs and cryptocurrencies are similar as they are both considered digital tokens. However, cryptocurrencies such as Bitcoin are fungible tokens. It means that a Bitcoin can simply be exchanged for another Bitcoin as two Bitcoins have the same value at any moment. Similarly, a dollar bill is considered fungible as it can be exchanged for another dollar bill. All fungible tokens are also divisible. Non-fungible tokens in comparison are unique and not interchangeable or divisible (Regner et al., 2019). The non-fungibility of NFTs and asset organization has opened new doors to a variety of use-cases including but not limited to digital art galleries and marketplaces (Whitaker, 2019), digital trading card games (Murray, 2021), and event ticketing (Regner et al., 2019). One of the most dominant use cases of NFT is crypto art - a rare digital art asset class that is tokenizable and unique. The digital token of crypto art resides on blockchain (Franceschet, 2020). In essence, crypto art enabled by blockchain technology, assigns unique value and ownership to digital creations. In contrast to traditional physical art, crypto art resides entirely in the digital domain. NFTs authenticate, prove ownership, and create scarcity for these works. Artists mint their art as NFTs, equipping them with digital certificates of authenticity. This innovation democratizes art by enabling direct artist-buyer connections and secure digital art trading among collectors. The digital assets can take many forms ranging from images to videos, and audios. Marketplaces such as OpenSea, Rarible, SuperRare, and Mintable provide an exchange environment for art collectors and artists to buy and sell crypto art. In 2017, two NFT projects received increased attention and became popular: CryptoKitties and CryptoPunks. The two projects include some of the historical NFT sales records. Nine assets in CryptoPunks collection sold for a total $16.9 million in Christie's in May 2021 (Franceschet, 2021). In March 2021, an artwork titled "The first 5000 Days" by a digital artist, Beeple, sold for $69.3 million at Christie's (Nadini et al., 2021).

The digital art marketplace and the possibility of keeping track of unique ownership of digital assets have brought new opportunities for the art community. Unlike the traditional world, in the digital art space, artists do not need to seek permission from galleries to showcase their artwork, and instead can show their

URI: https://hdl.handle.net/10125/106990
978-0-9981331-7-1

work anytime they want thanks to the NFT and the underlying blockchain technology.

Research on NFT is mostly focused on technical aspects pertaining to underlying technologies such as blockchain and smart contracts. NFT is a new and emerging technology; however, the transaction network of digital assets has increasingly expanded over the short period of time. The availability of this vast amount of public sales transaction data has created an unprecedented opportunity that calls for research that uncovers the underlying mechanism in which such networks evolve. The main goal in this research is to understand this new space of crypto art trading and exchange, which can eventually help identify the factors impacting the popularity and price of the assets, and overall, the structure of the trading network.

To explore the above aspects of crypto art space, we focus on the data from one of the most popular crypto art collections, CryptoPunks. The research questions we are seeking to answer are as follow:

Main question: "Does the structure of the trading network for CryptoPunks assets exhibit a level of decentralization comparable to the underlying NFT technology?"

Follow-up question: "What does the observed structure of the CryptoPunks trading network tell us about the underlying mechanisms?"

In order to answer the above questions, we explore the CryptoPunks trading networks from two aspects and aim to (1): identify key assets and collectors that are significant in the crypto art space; and (2): understand the structure of the crypto art space by identifying the linkages among the collectors of CryptoPunks assets and among the assets in the collection.

Our study is different from the existing literature in the following ways. First, we focus attention on the social structure of the digital assets and actors (including collectors and creators) in determining the popularity that potentially drives the asset prices and trading volume. Second, we perform a data-driven quantitative study based on real-time trading and sales data to carry out a two-fold methodological approach that is first applied to this domain. We borrow the citation analysis and social network analysis from bibliometrics and social network domain and apply them to the NFT space to explore the crypto art space trading and popularity development mechanism. While there are numerous bibliometric studies in various fields of science, to the best of our knowledge, no prior study has adopted this approach in the digital assets trading domain. Similarly, the applicability of the social network analysis approach and its potential in exploring the field of NFT trading space has not been previously explored.

2. Background

2.1. NFT Research

Market studies have shown increased attention to investigating the price correlation between NFT and cryptocurrency markets. Dowling (2021) studied the co-movement and spillover effects between NFT markets and cryptocurrencies. They found that there is a low volatility transmission between NFTs and cryptocurrencies. But there is evidence of co-movement between them. They suggest that common factors may impact both markets that result in co-movement (Dowling, 2021b). In another study, Dowling (2021a) provided evidence of pricing inefficiency in NFT markets and yet a rapid rise in value. The authors point out the potential market manipulations or other fraudulent activities that may impact the NFT markets (Dowling, 2021a). Although literature did not spot a causal relation between cryptocurrency and NFT prices, scholars have found that cryptocurrency prices could increase the hype around NFTs. Such a relationship was measured by Google search queries that were impacted by significant increase in major cryptocurrency prices such as Bitcoin and Ether (Pinto-Gutiérrez et al., 2022).

To understand the pricing mechanism of NFTs, economists have explored the NFT asset characteristics in determining their price. Nguyen (2022) found that dark-skinned CryptoPunks, although rarer, have significantly lower prices than their light-skinned and albino counterparts. They estimated that light skinned CryptoPunks trade for about 10% higher price than those of medium skin (Nguyen, 2022).

The current research on NFT seems to have focused on assessing the pricing mechanism and defining value in the digital assets space. The majority of research in this area uses practical approaches and is published in economics and finance journals (Bao et al., 2022). The approaches taken by those studies are based on economic views and pricing models driven by economic factors and criteria. What is missing in the previous studies is the structural view of NFT space based on the interactions among the collectors. In the specific NFT case of crypto art, if we equal pricing and assets' trading volume with one's success, the network analysis provides a good insight on different types of actors and their interactions, which eventually opens up new avenues that lead to identifying and predicting success in crypto art. Is the centrality of an actor (creator) in the network a measure of the actor's success? Does the actor's connection to prestigious or popular collectors with high betweenness centrality measure lead to the actor's success? Answers to these questions may uncover the mechanism under which success is achieved, which may prove that criteria other than quality are influential when it comes to success in digital art. Research in art success in spaces other than crypto art has shown that mechanisms that drive success and reputation in art space can be linked to measures such as connections with reputable galleries and collectors, which are not relevant to creativity (Fraiberger et al., 2018; Mitali and Ingram, 2018). The crypto art space is founded on decentralized blockchain technology. In a decentralized community of artists and collectors, one would expect creativity to be the sole driver of fame as the power imbalance in the network would be diminished because of the decentralized nature of the technology. However, the technology can also facilitate abusing the system by actors with malicious intention to artificially inflate the price and thus creating the false perception of items' popularity.

In the following we review the studies that can help us identify a method to construct and analyze the interactions network of collectors and assets.

2.2. Scholarly Network and Crypto art

Crypto art space can be compared to the scholarly publication system in several ways. Although the two spaces differ in many ways, they still share common characteristics specifically in three phases involving creation, presentation, and endorsement (Franceschet et al., 2021). In this context we are only considering the collectors in the art network and not the creators. That being said, if in the scholarly network, we focus on the citation behavior only, then the artwork is comparable to a research paper where collectors collect the artwork and researchers cite the paper. While scientific publications gain endorsement through citations, the number of which serves as a popularity measure, artworks are endorsed and gain popularity by receiving a bid from collectors (Franceschet et al., 2021). The main difference between these two types of networks is that in order to cite an article, authors need to do so in a paper in progress; while as for collectors, the artwork can be collected without any other restriction.

2.3. Bibliometric Analysis

Bibliometric analysis in scientific domains helps to identify key publications and/or authors that have significant contribution to the field (Hota et al., 2020). It also helps to discover growth patterns of the field over time by tracking papers' popularity and the conceptual evolution of the field over time (Tandon et al., 2021). The bibliometric approach has been adopted by researchers from various disciplines such as entrepreneurship (Hota et al., 2020), blockchain (Tandon et al., 2021), management (Ferreira, 2018), and information systems (Yang et al., 2015; Khan and Wood, 2016). Bibliometrics involves various techniques that each have their strengths and weaknesses (Tandon et al., 2021). Among them. co-citation analysis is a commonly used approach. Co-citation of two articles means that there are occurrences where two articles are cited by other independent articles (Shiau et al., 2017). White and Griffith use authors as the unit of analysis in the mapping of information science areas (White and Griffith, 1981). They consider the co-citation of authors as the measure of distance between two authors. In their paper, the co-citation of authors is defined as the number of times two authors are cited together rather than citing the same article together (White and Griffith, 1981). Another approach in bibliometric analysis is called bibliographic coupling. Bibliographic coupling of documents measures the frequency of which two documents cite the same document (Kessler, 1963). This measure has been adopted to use the authors as the unit of analysis; thus, two authors can be bibliographically coupled if they cite the same article in the paper that they published. In a paper bibliographic coupling, a high value indicates the similarity in subject relationship between the two papers (Chang et al., 2015). Similarly, the high value of authors bibliographic coupling measure indicates the subject similarity between the two authors (Rathinam and Sankar, 2019). Studies have argued that author bibliographic coupling complements document co-citation approach to provide a more comprehensive overview of the intellectual structure of a scientific field (Zhao and Strotmann, 2008a, 2008b).

In the NFT and specifically crypto art space, a digital asset (an artwork) can be equivalent to a document or an article. The difference is that the citation does not occur in crypto art space; instead, the assets can be traded or purchased and transferred from one collector to another collector, where the latter will be the new sole owner of the asset. Hence, we can define co-ownership of assets as a counterpart measure of the co-citation of articles in the following way: co-ownership of assets identifies occurrences where two assets are owned by the same collector at any point of time. Note that another difference between the original co-citation and co-ownership concepts is that the citation link remains forever, however, the ownership changes over time; the old ownership expires when a new collector owns the asset, as in most cases an asset can only be owned by one person at any point of time.

Similar to the asset co-ownership network that derives from the document co-citation concept, we can define a collector co-ownership network that is equivalent to author bibliographic coupling in the bibliometric domain. That said, two collectors are coupled by ownership if they own the same asset at two different points of time.

2.4. Social Network Analysis

Many of the studies that perform bibliometric analysis use social network analysis (SNA) as a complementary approach to co-citation analysis (Hota et al., 2020). SNA uses three prominent centrality measures to understand network structures and identify key actors in a network. Accompanied with co-citation analysis, SNA can identify key articles, or key contributors and their influence through centrality measures in a knowledge network (Hota et al., 2020). The three prominent centrality measures used in SNA include degree centrality, closeness centrality, and betweenness centrality (Newman, 2008). Degree centrality simply refers to the number of links an actor has with other actors in the same network. This centrality is commonly used to measure the prestige and influence of journals in a discipline such as Information Systems (Chan et al., 2015; Polites and Watson, 2009). Closeness centrality of an actor denotes the reciprocal of the mean geodesic distance of the actor to all reachable actors in the network. Actors that are more central and have shorter distance to other actors in the network have higher closeness centrality (Newman, 2008). Closeness centrality has been used to measure the cognitive diversity of a scientific domain (Rafols and Meyer, 2007). Betweenness centrality measures the number of times a certain actor acts as a broker connecting two other actors through a geodesic path. It acts as the measure of an actor's power over controlling the flow of information in the network (Newman, 2008). Betweenness centrality has been adopted in a case where the interdisciplinarity of a discipline was being investigated (Leydesdorff, 2007). SNA has been applied in Information Systems (IS) research to study network structures and dynamics. For example, Guo et al. (2016) used random-walk betweenness to assess individual node positions in malware propagation (Guo et al., 2016). Pak and Zhou (2015) explored centrality changes in online gaming social networks, revealing distinct patterns between deceivers and truth-tellers during interactions (Pak and Zhou, 2015). The centrality measures used in SNA have potential to provide insights on the key actors in an NFT trading network. The actors in this network involve assets and collectors instead of articles and authors that are commonly used in bibliometric research. To the best of our knowledge, SNA and bibliometric analysis have not been adopted in a study involving NFT trading networks.

Some real-world networks such as the World Wide Web network, social networks, or scientific collaboration networks seem to demonstrate "preferential attachment" behavior, which means new members prefer to attach to the existing members that are already well connected (Hein et al., 2006). Preferential attachment property of networks leads to emergence of "scale-free" networks. Scale-free networks were first introduced by Barabási and Bonabeau, (2003), and since then became a prominent phenomenon of study in analyzing real-world networks. In scale-free networks, the degree of nodes follows a power law distribution (Barabási and Bonabeau, 2003). In the IS field, scale-free networks have been observed in diverse contexts. For example, Zhang et al. (2016) identified scale-free networks in online brand advertising's implicit brand–brand networks (Zhang et al., 2016). Strozzi et al. (2019) found a scale-free network in the patient choice network in healthcare service planning (Strozzi et al., 2019). Zhao et al. (2021) introduced a novel approach for node representation in networks with long-tail node degrees, reflecting power law distribution in social recommendation contexts (Zhao et al., 2021). Wiesneth (2016) noted dynamic network structures with preferential attachment and power law degree distribution in Enterprise Social Networks (ESNs) (Wiesneth, 2016). Khan and Wood (2016) conducted a social network analysis of the information technology management (ITM) domain, revealing power law distribution with new connections favoring well-connected nodes (Khan and Wood, 2016). A study on social bots' influence on public opinion found that even a small number of bots (around 2-2.5% of actors) could significantly impact perceived majority opinion, especially with preferential attachment strategies (Ross et al., 2019).

Barthelemy (2004) analyzed large complex networks and found that the betweenness centrality in such networks has power law distribution. Betweenness centrality distribution has also been studied in transportation network domains. Altshuler et al. (2011) found that the distributions of congestion on junctions have power law nature, which implies that a few nodes have arbitrary large congestion (Altshuler et al., 2011). A similar pattern has been observed in scientific collaboration and co-citation networks (Lin et al., 2009). Scale-free networks are emergent in the market domain as well. Tseng et al studied the financial markets as complex systems and based on the finding they suggest that the scale-free nature of such networks rely on the institutional design and the structure of the market rather than the traders' strategy (Tseng et al., 2009). Similar studies have confirmed the same pattern in market investment and international trading (Baskaran et al., 2011; Garlaschelli et al., 2005).

The previous research have shown that the study of power law distribution and examining scale-free network structure give us insight on the working mechanisms in the network; as the existence of preferential attachment leads to a few hubs or core actors that have the power to manipulate some measures in the network, such as the price of stock or bilateral trade in sparse networks (Baskaran et al., 2011; Tseng et al., 2009). The preferential attachment has been studied in the context of cryptocurrency transactions on networks such as Ethereum and Bitcoin (Aspembitova et al., 2019; De Collibus et al., 2021). We argue that NFT networks may show different behavior mainly due to their core difference to other crypto assets as each NFT is unique and non-fungible. Hence in this paper, we explore one of the NFT trading networks to examine this supposition and discover if the network shows a similar power law behavior.

In the following section we explain in detail how we adopted the aforementioned two approaches in our research method to identify the network structure of crypto art trades.

3. Methodology

3.1. Data Collection

We collected data from the CryptoPunks collection, which was renowned as the most popular crypto art collection at the time due to its rarity, historical significance, and high market value. With only 10,000 unique avatars on the Ethereum blockchain, CryptoPunks were in high demand among collectors. Recent record-breaking sales, like CryptoPunk 9997 for $4.35 million and "COVID Alien" for $11.75 million, underscored their immense worth. Their popularity extended beyond NFT platforms, with some CryptoPunks finding their way into major art institutions. Around the time of data collection, there were 3,121 users holding CryptoPunks in their Ethereum wallets, cementing CryptoPunks' status as the leading crypto art collection (Artsy Editorial, 2021).

To collect the data, we used the OpenSea API. The Endpoints in this API include NFT collections, assets (NFTs), and events. Events in OpenSea can take various forms. The type of event that is of interest to our study is the successful sales transactions. This endpoint in the OpeanSea API is called *successful*. Using Python scripts, we collected *successful* transactions in the CryptoPunks collection. The event object includes data about the asset being sold or transferred, the date when the transaction was recorded, the accounts that were associated with the transaction, the payment information that includes the payment token (ETH, WETH or DAI), the quantity, and the total price, which may include any royalties. To be able to construct the transaction sales network, we also collected information about all the assets in this collection. Each asset data includes the following fields: token id, image URL, last sale date if applicable, asset traits, and the smart contract address. An example of a CryptoPunks asset on the OpenSea platform is shown in Figure 1.

In total, we collected all the 10,000 assets that exist in CryptoPunks collection along with 10,050 successful sales as of October 11th, 2021.

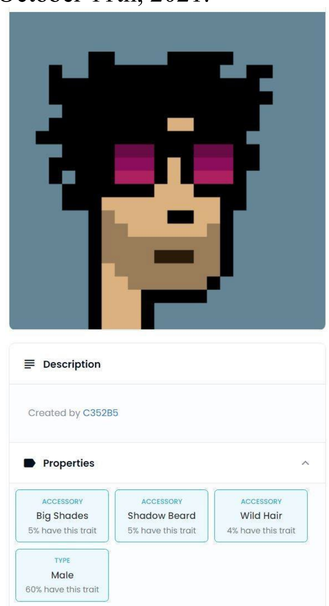

Figure 1. CryptoPunk #9766 and its traits. Source: opensea.io

3.2. Building the Asset Co-ownership Matrix

To build the asset co-ownership matrix, we adopted the co-citation measure from bibliographic analysis and considered assets as the unit of analysis. Thus, we define an undirected link between two assets if they are owned by the same collector at any point in time. The assets do not have to be necessarily owned together at the same time, although the ownership timeframes may overlap as well. Each edge connecting any two assets in this network has a weight associated with it that identifies the frequency of the two assets being owned by the same collector.

3.3. Building the Collector Co-ownership Matrix

We adopted author bibliographic coupling as a complement measure to the assets co-ownership measure. We define two collectors being coupled when they own the same asset at different points in time. Thus, we consider collector as the unit of analysis and define collector co-ownership as the frequency of two collectors owning the same asset at two different points in time. Of course, the ownership time periods of the same asset cannot overlap due to the asset being unique and being owned by one owner at any time in the CryptoPunks collection. Similar to asset co-ownership, each edge in this network has a weight measure as well that indicates the frequency at which two collectors own the same asset.

3.4. Studying the power law distribution

If betweenness centrality in the co-ownership networks aligns with a power law distribution for collectors, as per our research question on NFT decentralization, it implies a core group of influential collectors. We propose hypothesis 0 and test this assumption. Deviations from this distribution could suggest a different network structure, contrary to NFT decentralization expectations. Thus, our hypotheses are as follows:

- *H0:* data is generated from a power law distribution.
- *H1:* data is not generated from a power law distribution.

The data is fit to the power law distribution model using the poweRlaw package in R software (Gillespie, 2014). Then, to test whether the data actually follows a power law distribution, we used a goodness-of-fit test via a bootstrapping procedure. If the p value is large, then we can argue that the difference between the actual data and the model is due to statistical fluctuations.

4. Results

4.1. Asset Co-ownership Analysis

The asset co-ownership matrix resulted in 3470 nodes and 76920 undirected edges. Table 1 provides a summary of several measures pertaining to this matrix.

Table 1. Graph measures of the asset co-ownership matrix.

Measure	Value
Average Weighted Degree	48.269
Diameter	10
Average Path length	3.19
Density	0.013
Modularity	0.626
Number of Communities	82
Average Clustering Coefficient	0.771

Figure 2 presents the biggest top five partitions in the asset co-ownership graph. The top 5 partitions account for 64.38% of the nodes in the graph (total of 2234 nodes), and 51.51% of the edges (total of 39618 edges).
The majority of the edges have weight of 1, meaning that most of the assets are co-owned with only one other asset. Seventy-one assets were co-owned five or more times. The densest component in this graph is the orange component (in the center of the image), where most of the assets are co-owned together, and each asset is co-owned with more than one other asset (Figure 2).

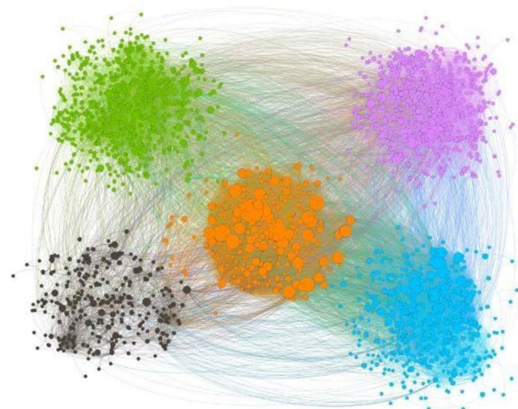

Figure 2. The asset co-ownership network with the top 5 partitions. Nodes are color-coded by module.

4.2. Collector Co-ownership matrix

The collector co-ownership matrix resulted in 2640 nodes and 9418 undirected edges. Table 2 provides a summary of several measures pertaining to this matrix. Figure 3 presents the biggest top five partitions in the collector co-ownership graph. The top five partitions in this graph account for 42.58% of the nodes (total of 1124 nodes) and 37.65% of the edges (total of 3248 edges) (Figure 3).

Table 2. Graph measures of the collector co-ownership matrix.

Measure	Value
Average Weighted Degree	6.945
Diameter	11
Average Path length	3.58
Density	0.013
Modularity	0.491
Number of Communities	102
Average Clustering Coefficient	0.655

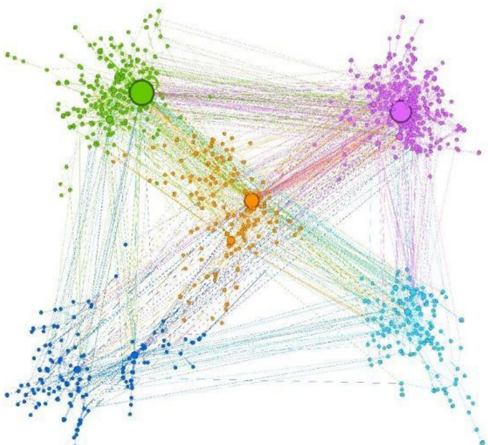

Figure 3. The collector co-ownership network with the top 5 partitions shown in different colors.

4.3. Social network analysis

The results of power law analysis of the betweenness centrality of nodes in the asset and collector co-ownership networks are shown in figure 4 and Figure 5 respectively.

The bootstrap procedure was done to identify whether the distribution of the betweenness centrality in this network actually fits the power law distribution or the difference between the two is beyond the statistical fluctuations. Figures 6 and 7 show the result of the bootstrap procedure for the asset and collector co-ownership networks respectively. In both graphs, we observe high cumulative p-values, with the final p-value being 0.39 for one graph and 1 for the other. Moreover, both graphs in figures 6 and 7 show that as the sample size increases, the p-values tend to stabilize, suggesting that the distribution of betweenness centrality in the co-ownership networks aligns well with a power law distribution. In line with our research question and the decentralized nature of NFT technology, our results imply that the CryptoPunks trading network may not exhibit a high degree of decentralization.

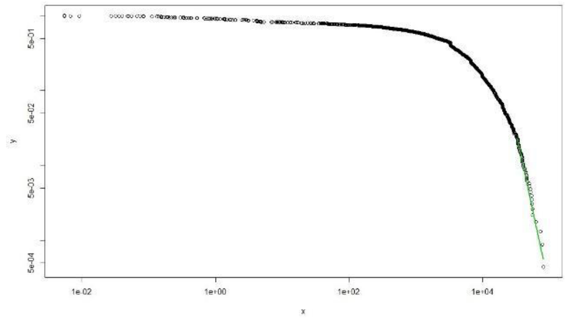

Figure 4. The fitted power law (green line), and the distribution of the betweenness centrality in the asset co-ownership graph.

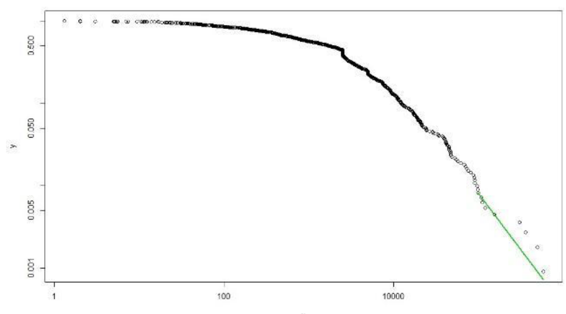

Figure 5. The fitted power law (green line), and the distribution of the betweenness centrality in the collector co-ownership graph.

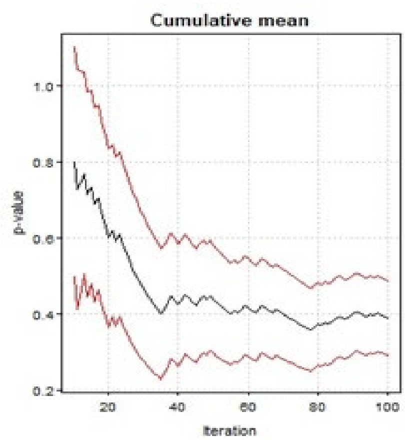

Figure 6. Results of the power law model estimate from the bootstrap procedure for the betweenness centrality in the asset co-ownership graph. (Confidence intervals: 95%).

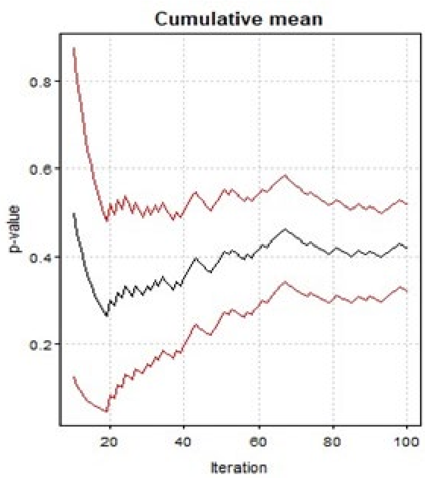

Figure 7. Results of the power law model estimate from the bootstrap procedure for the betweenness centrality in the collector co-ownership graph. (Confidence intervals: 95%)

5. Discussion

The bibliometric analysis of the network helped us identify two graphs with nodes representing the assets and the collectors. Our analysis reveals that both networks exhibit a scale-free structure, where a few nodes hold significant centrality. This finding is intriguing because web 3.0 spaces prioritize decentralization and democratization. However, we observe the emergence of preferential attachment, indicating that trading volume may correlate with collectors' popularity and past interactions. Further research is needed to explore this supposition. If confirmed, this trend implies that artists may need to connect with well-connected collectors, raising questions about NFT adoption's core mission of democratizing art opportunities.

Building on the insights gained from prior research in the field of Information Systems, particularly the studies on knowledge networks and the investigation into the influence of social bots on public opinion, our study extends the application of network analysis to the realm of crypto art trading networks. While the domains differ, we draw upon the methodologies and concepts developed in IS studies to explore the intricate dynamics of popularity and pricing within the CryptoPunks collection.

However, our research brings a novel dimension to the analysis. Unlike traditional IS networks, crypto art trading networks involve unique digital assets and collectors, each with distinct characteristics. In this context, we proposed a methodology that adapts established network analysis techniques to account for the non-fungible nature of crypto art assets. By introducing the concept of co-ownership of assets as a counterpart measure to traditional co-citation, we shed light on how collectors influence the network's structure.

Our study's contribution lies in two key aspects. First, it deepens our understanding of crypto art trading networks, revealing patterns of preferential attachment and a power law distribution in co-ownership relationships. Second, it highlights the relevance of established IS concepts in deciphering the decentralized and evolving landscape of digital creativity and commerce. By bridging these two domains, our research not only uncovers the mechanics of crypto art popularity but also underscores the adaptability of IS methodologies to emerging digital markets. With an emphasis on providing insights beyond surface-level analyses, our study aims to uncover the mechanisms driving the crypto art trading landscape. While our research introduces key insights into these dynamics, our focus extends beyond novelty to the realm of broader significance. By initiating inquiries into complex aspects, including the potential presence of anomalies like colluding or wash trading behavior, we establish a foundational understanding that lays the groundwork for future exploration. We envision our findings as a catalyst for future investigations, encouraging researchers to delve into the multifaceted landscape of digital creativity and commerce while recognizing the influence of collectors and the uniqueness of digital assets.

5.1. Limitations and future directions

This study is only limited to one of the NFT collections, CryptoPunks. Thus, the result may not be generalized to the entire crypto art trading networks. However, we believe that the findings open doors for future investigations that are necessary to determine if the discovered pattern holds in other crypt art collections as well.

In this study, we did not intend to uncover factors that contribute to the popularity of crypto art assets; rather, we ruled out the factors that do not play a significant role in driving the asset popularity. Given the current findings regarding the heavy-tailed distribution of asset popularity, future research should investigate exceptional cases where asset popularity may be due to factors other than the social network factors such as preferential attachment.

It is also important to note that our intention was not to develop a model for asset price prediction. However, this sounds like an interesting future direction to take. Another future path worth taking is investigating the transaction network over time to unfold the evolving pattern observed in the network. Thus, we suggest conducting a longitudinal study of the NFT trades network, which will uncover potentially insightful patterns showing the formation of preferential attachment behavior.

6. Conclusion

In this paper, we conducted a data-driven quantitative study of trading networks in an NFT collection. We showed the applicability of social network analysis in combination with bibliographic metrics to explore the co-ownership network structure for both assets and collectors; and found that despite the distributed nature of the underlying technology for asset organization, the co-ownership distribution is still skewed and heavy-tailed. This essentially means that like in a traditional market of tangible goods, more powerful traders can leverage higher earnings. As one of the few quantitative studies in the NFT domain, we hope that this study opens doors for more research in this emerging area to dig deeper into the dominant actors in the network, and through a longitudinal study, discover the mechanism under which the network evolves into demonstrating such a heavy-tailed distributions of assets and collectors' co-ownership degree. Such research directions lead to identifying patterns of NFT adoption and discovering factors impacting popularity, trading volume, and price of digital assets.

7. References

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