# Clubs of wallets: a dive into the mesoscopic features of NFT transaction networks

Alessia Galdeman[1], Lucio La Cava[2], Matteo Zignani[1], Andrea Tagarelli[2], and Sabrina Gaito[1]
[1] Department of Computer Science - University of Milan
Via Celoria, 18 20133 Milan, Italy
[2] Department of Computer Engineering, Modeling, Electronics, and Systems Engineering (DIMES)
University of Calabria, 87036, Rende, Italy

*Non-Fungible Tokens*, better known as NFTs, represent a diffusion process of digital assets through the Internet supported by blockchain technology in the Web3 context. By exploiting the availability of smart contracts and cryptocurrencies, NFTs associate an owner with a unique asset — whether digital or physical — such as art pieces, in-game items, or even objects in the metaverse. Their potential attracted the attention of users and investors early on, eventually becoming mainstream in mid-late 2021 when the NFT ecosystem exceeded all expectations regarding notoriety and cryptocurrency trading volumes. Despite this phenomenon has also attracted considerable interest in the academic community, to date and to the best of our knowledge, no work exists today aimed at analyzing the main mesoscopic features of the trading network(s) arising from the NFTs flow, from which valuable details for the understanding of such a novel landscape might emerge.

In this regard, the dataset collected and analyzed by Nadini *et al.* [1] in their seminal work represents a valuable entry point to analyze the NFT markets from several perspectives. It contains more than 6M transactions depicting NFT sales between 532 945 different users relying on five different markets, namely Cryptokitties, OpenSea, Decentraland, Gods Unchained, and Atomic. As reported in Figure 1, the dataset covers a period of time ranging from November 23, 2017 (the date of the first Cryptokitty sale) to April 27, 2021 (the date of the last captured transaction).

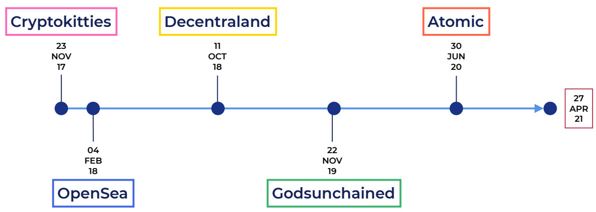


Fig. 1. Transaction collection period timeline: for each market the time of the first observed sale is reported.

Given the significance and freshness of the aforementioned dataset, we decided to derive from it a network model capable of shaping transactions between users within each market, thus allowing us to analyze their main patterns. Specifically, we defined a directed weighted graph $G_m = (V_m, E_m, w_m)$ for each market $m$, where $V_m$ represents the set of users that performed at least one operation on market $m$, $E_m$ is the set of edges $(u, v)$ denoting a sale from user $u$ to user $v$, and $w_m : E_m \to \mathbb{R}$ is a weighting function that assigns the number of sales from user $u$ to user $v$ on each edge $(u, v)$.

We report the main traits (i.e., number of nodes and edges) of our market graphs in Table 1, highlighting that also the number of sales is a differentiating factor, along with the temporal coverage.

| Market | Order | Size |
|---|---|---|
| Cryptokitties | 99 984 | 481 540 |
| OpenSea | 214 238 | 965 496 |
| Decentraland | 4 747 | 11 757 |
| Godsunchained | 2 535 | 4 085 |
| Atomic | 263 453 | 1 719 458 |

Table 1. Main characteristics of the market graphs inferred from the transaction data.

From a qualitative perspective, it should be noted that the markets also differ in terms of purpose, e.g., Cryptokitties and Godsunchained are blockchain-based games, while Atomic and OpenSea are generic and multi-categorical NFT markets. This diversification reflects in the distribution of the categories over the transactions, as shown in Figure 2. On the one hand, we observe that Cryptokitties, Godsunchained, and Decentraland are characterized by the trading of single-category NFTs, i.e., *Art* for Cryptokitties, *Games* for Godsunchained, and *Metaverse* for Decentraland, whereas, on the other hand, we spot various categories traded in Atomic and OpenSea, with a dominance of *Games*, *Collectible*, and *Art*.

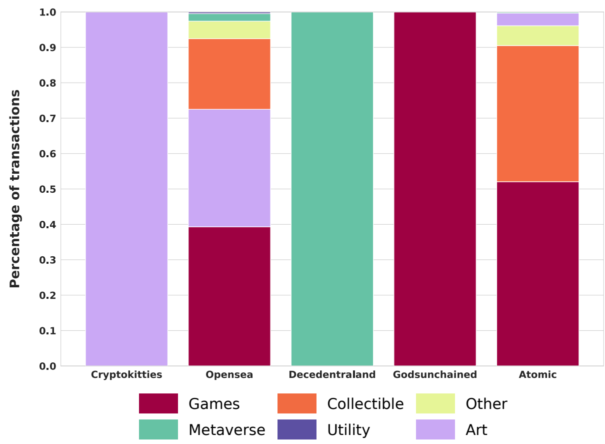


Fig. 2. Distribution of the categories traded in the considered markets.

Based on the above observations, our goal is therefore to study the presence of latent or explicit patterns common to these markets, which, although aimed at different purposes, are united by the use of blockchains for NFT transactions. In this regard, we would like to investigate whether and to what extent traders are organized in tightly-knit communities, hence concentrating NFT exchanges within the same group, while having fewer connections with users belonging to other groups, or communities.

To gain a mesoscopic perspective on the transactions occurring within each market, we relied on the well-known *In-*

| Market | Total | Filtered | Conductance |
|---|---|---|---|
| Cryptokitties | 7 757 | 5 751 | 686 |
| OpenSea | 12 876 | 7 621 | 115 |
| Decentraland | 570 | 370 | 370 |
| Godsunchained | 434 | 5 | 5 |
| Atomic | 10 373 | 7 858 | 300 |

Table 2. Communities detected via the Infomap algorithm in the five NFT markets under analysis.

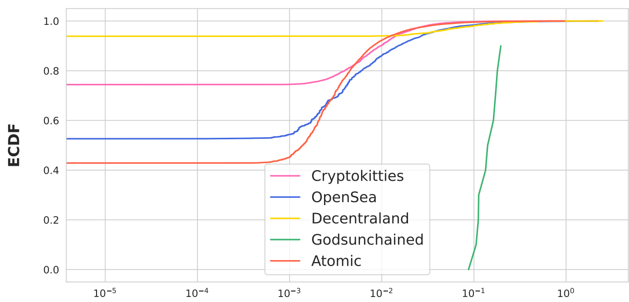


Fig. 3. Empirical distribution of the pairwise conductance values for the selected communities in each market.

*foMap* community detection algorithm [2], which is based on the duality between finding communities and minimizing the description length of a random-walker in a network. For each market-graph, we report the overall number of community structures yielded by Infomap, and the number of remaining communities after having pruned the ones having at most two nodes in the "Total" and "Filtered" columns of Table 2, respectively.

To measure the magnitude of flows between the obtained communities, we resorted to the *conductance* measure [3], which is the ratio between the cut size and the volume of the smaller set (e.g., community). In this regard, we took into account the strong heterogeneity in terms of size in the communities returned by Infomap, which would make the complete pairwise computation of the conductance practically pointless. Therefore, to overcome this issue, we considered the communities having a *reach*, i.e., the total number of users, above a $p\%$ of the user base in the considered market-graph. Specifically, by selecting $p = 50$, we were able to calculate a meaningful pairwise conductance score between $686, 115, 370, 5, 300$ communities, respectively for the Cryptokitties, OpenSea, Decentraland, Godsunchained, and Atomic markets. In this regard, we point out that the number of communities considered in the Godsunchained and Decentraland cases corresponds to the total number of filtered communities, to avoid considering communities that would be too small. We report the empirical distribution of the pairwise conductance values for each market-graph in Figure 3, from which we can observe that the Cryptokitties, Atomic and OpenSea conductance distributions follow the same shape, while Decentraland and Godsunchained differ from the others.

Finally, to gain further insights into the motifs between trader communities in the considered NFT markets, we analyzed the inter-community transaction flows, also considering those users exhibiting anomalous volumes of trading (i.e., overall expense $> 3\sigma$ w.r.t. the average expense of the users that purchase NFTs outside the community they belong to), thus identifiable as outliers. We report the main

| OpenSea | % Total | % Cross | % Outlier |
|---|---|---|---|
| Art | 33.21 | 44.51 | 62.83 |
| Collectible | 19.94 | 8.66 | 10.32 |
| Games | 39.29 | 24.15 | 12.68 |
| Metaverse | 2.15 | 3.88 | 4.18 |
| Other | 4.95 | 8.17 | 8.88 |
| Utility | 0.45 | 0.63 | 1.11 |

Table 3. Distribution of categories in Opensea transactions. Cross, resp. Outlier., indicate the inter-community transactions carried out by all users, resp. users remarked as outliers.

| Atomic | % Total | % Cross | % Outlier |
|---|---|---|---|
| Art | 3.57 | 4.05 | 5.2 |
| Collectible | 38.47 | 36.33 | 55.41 |
| Games | 52.04 | 52.99 | 34.6 |
| Metaverse | 0.33 | 0.43 | 0.08 |
| Other | 5.6 | 6.19 | 4.71 |
| Utility | $5{\cdot}10^{-4}$ | $4{\cdot}10^{-4}$ | 0 |

Table 4. Distribution of categories in Atomic transactions. Cross, resp. Outlier., indicate to the inter-community transactions carried out by all users, resp. users remarked as outliers.

results of our investigations in Tables 3-4. As concerns the first point, we observed that in the OpenSea market inter-community transactions follow a distribution of categories that remarkably diverges from that of the market as a whole; moreover, we report that the latter trait is strongly accentuated when considering the categories traded by outliers. Furthermore, we noted that the inter-community transactions in the Atomic layer follow the same shape as the whole market's transactions, whereas the category distribution of the transactions involving outliers sets up in a slightly different shape.

The investigations carried out by us so far have shed light on the existence of non-negligible mesoscopic phenomena within the transaction networks involving NFTs in different markets. The emergence of hints towards potential small world traits and the community specialization and/or independence detected through the Infomap algorithm paves the way for new and fascinating studies of the phenomena arising from the crypto world and the Web3.

In this regard, as an ongoing work, we are considering more robust techniques to carry out a wide range of analyses from a mesoscopic perspective, so as to unveil the underlying footprint of the NFT exchange communities to foster a better characterization of the same.


[1] M. Nadini, L. Alessandretti, F. Di Giacinto, M. Martino, L. M. Aiello, and A. Baronchelli, "Mapping the NFT revolution: market trends, trade networks, and visual features," *Scientific reports*, vol. 11, no. 1, pp. 1–11, 2021.

[2] M. Rosvall and C. T. Bergstrom, "Maps of random walks on complex networks reveal community structure," *Proceedings of the National Academy of Sciences*, vol. 105, no. 4, pp. 1118–1123, 2008.

[3] D. Gleich, "Hierarchical directed spectral graph partitioning," *Information Networks*, vol. 443, 2006.