CX4242 Project Report: Abnormality Detection in NFT Marketplace

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1 Introduction

With the popularization of cryptocurrencies, abnormal trading behaviors have become more prevalent. Our objective is to identify suspicious market manipulation specifically in the NFT (non-fungible token) marketplace using statistical microstructure and network analysis displayed through interactive visualizations.

The decentralized nature of blockchain makes it impossible to regulate suspicious behaviors and it's thus important to create tools that can deliver transparent and liquid pre-trade and post-trade information to all levels of NFT investors, supporting identification of unnecessary risks while creating a compelling case for improved security scrutiny.

2 Problem Definition

The problem to be solved is the lack of reachable services to validate prices and identify fraud-prone NFT collections and users. Our solution employs suspicious microstructure indicators, network centrality analysis, and interactive visualizations that clearly highlight abnormal tradings. Our visualizations are a completely novel functionality as there is currently no software that applies similar approaches for NFT market.

3 Survey

For background knowledge, we survey literature that summarizes the background history of NFTs. Ante [1] and Dowling [2] overview the development of the NFT market, Ethereum blockchain, and cryptocurrencies. These studies are supplemented by Cornelius's [3] discussion about NFT fraud traceability and identification and Putnins' [4] description of market manipulation, which all reach a consensus that NFT market manipulation is a serious problem worth analysis and attention. Specifically, Imisiker et al. [5] and Qin et al. [6] detect security risks in blockchain washing trading activities and blockchain extractable value, proving again that suspicious manipulation behaviors are prevalent in this virtual space. The severity of such problems inspire us to design reachable services that can help investors assess risk with quantitative measures and interactive interfaces, such as how Nadini et al. [7] visually analyzes NFT market revolutions and trading networks.

We then survey more academic papers with practical fraud detection methods in traditional financial markets. Xu et. al [8] outlines a metrics-based detection method for pump and dump schemes but fails to capture instances of more secretive fraud. Monamo et. al [9] summarizes the use of unsupervised learning in Bitcoin fraud detection, opening the possibility of using machine learning for NFT trading data analysis. Chen et. al [10] identifies abnormal bitcoin exchange structures with leaked transaction history, which matches our goal of discovering irregular behaviors through trade networks. Wu et. al [11] presents a literature review on understanding cryptocurrency transaction networks and divides crypto-related network techniques into three major sections, providing a framework for building a network graph. Similarly, Camino et. al [12] and Zhai et. al [13] present methods to analyze cryptocurrency transactions using unsupervised learning with real-world case studies and a hybrid ML model combining SVM and HMM that detects disruptive market activities, providing us an additional approach to detect suspicious behaviors. Finally, Phillips and Heidi [14] use clustering algorithms to categorize crypto-related online scams and analyze blockchain campaigns structures, which motivates us to use graph and cluster based approaches to identify fraud.

These literature analyses seem promising, but matured fraud detection models in the NFT market are lacking. Many methods proposed in the following surveys lack implementation or experiments in real world scenarios and are mostly scientific research findings that cannot be utilized as reachable services. Chen et. al [15] and Zhang et. al [16] present learning algorithms in data-driven approaches that show and justify evidence for stock price manipulation, which is useful as foundational knowledge for a ML approach but is limited in scope, as stock markets do not necessarily correspond to NFT markets. Golmohammadi et. al [17] and Kumar et. al [18] also utilize machine learning for stock market trend prediction, which cement our understanding of trends in financial markets and abnormal behaviors in financial trading and transactions, given the many similarities between the stock market and the NFT market.

4 Proposed Method

The novelty of the NFT marketplace generates challenges for finding authoritative references, but it also allows for endless possibilities. Our design supports innovations from three domains: *synthetic token-centric and user-centric analyses*, design of *innovative suspicious microstructure indicators* cross validated by *graph-based network analyses*, and an *interactive time-based heatmap and market networks* serving as representative explanations of our findings. We introduce these innovations in detail in the following subsections.

4.1 Data Collection & Preprocessing

An NFT is a digital art piece stored on a blockchain and is created in collections with a specific contract address. Each NFT collection contains various NFTs with token IDs ranging from 1 to 10000, or even more. Each user account in the marketplace has a unique wallet address and may sell or transfer tokens.

Our datasets come entirely from Moralis.io, an API that allows us to retrieve real time data from OpenSea, a leading marketplace in the NFT-space. Calling the API iteratively with JavaScript, we collect the transaction history for each of the 14 most popular NFT collections on OpenSea. resulting in a total of 511,767 transaction records with 115,869 distinct wallets, which is a large enough dataset given the novelty of the NFT market, and we have cross-validated this dataset with real online data.

To support identification of suspicious behaviors, we upload the database into SQLite, creating a database of 487 MB, using SQL commands and Jupyter Notebook to combine transactions of all 14 collections and extract a list of distinct wallets. The all-transaction table contains collection/token ids, block timestamp and the buyer/seller addresses, allowing us to extract transaction histories of a single collection and analyze the vitality distribution based on time. The all-wallets table is created by filtering distinct wallet-hash from to-address and from-address in the order book, allowing us to observe abnormal user behaviors.

4.2 Abnormality Detection Algorithms

The motivations behind market manipulation include market making (inflating item price), rate making (increasing popularity), and incentivizing (getting trading rewards) [19]. For example, LooksRare, another NFT marketplace leader, attempts to lure users by offering digital rewards to accounts with daily largest trading volume. This policy entices more users to profit from high frequency and large volume of illusory transactions between linked accounts. Such behaviors are identified as market manipulation in the stock market and are strictly regulated. However, these actions are still poorly monitored in the NFT market and are not flagged as such, adding innovation and value to our research.

We employ two approaches: **abnormality indicator analysis** that identifies NFT collections/tokens with suspiciously-high trading frequency and **network centrality analysis** which locates the most influential active users in a system. Abnormal index is designed base on financial principles and trading characteristics of market manipulators. It can be simple and intuitive, but is the most effective and accurate approach. On the other hand, we utilize network analysis algorithms in an exploratory manner. The complex algorithms we use innovatively may or may not be successful, and their credibility and reliability still need to be proved. But we think such exploration is really important for a new field such as fraud detection in the NFT market.

We have also considered using machine learning models to do even more complex analysis. However, the decentralized nature of blockchain protects user information and generates only a brief proof of transaction histories, thus creating a lack of useful features for a machine to learn patterns. Simultaneously, due to the anonymous nature of the NFT marketplace, there is a lack of concrete evidence to validate the prediction results. Because of the scarcity of research in this domain, our main goal is to uncover insights in fraudulent behavior patterns, serving as a cornerstone for future studies; instead of pursuing accurate predictions, statistical inference is a more appropriate approach.

4.2.1 *Abnormality Indicators*

Abnormality indicators rely on behavioral properties of market manipulation, enabling identification of suspicious NFT collections and tokens. The first index we propose is the **skewed turnover rate**. Share turnover rate measures liquidity of the stock market, whereas, in the NFT market, liquidity is measured by *total number of transactions/total number of distinct wallets involved*. Unlike the stock market, higher liquidity indicates higher probability of artificial market manipulation because under normal conditions, the NFT transaction frequency is low as shown in figure 1 since most people buy NFTs for the ownership of the artwork instead of speculating for profit. To increase accuracy and complexity, we plan to introduce a skewness factor that takes the collection popularity into account in following experiments.

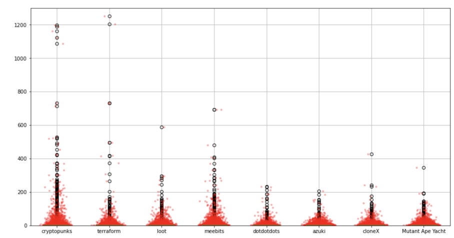

Figure 1: All Collections Have Large Amount of Users Trading with Low Frequency

The second index we propose is **daily overactive token count**. We analyze transaction records on a daily basis, making the assumption that an overwhelming amount of trading activities within a day is a sign of wash trading. Thus, we count the number of transactions for each token by day and label the ones over a threshold as abnormal objects. We will define the threshold in the following experiments.

4.2.2 Network Centrality Analysis

Network centrality analysis offers user-centric insights, enabling identification of suspicious traders. Giving a directed-graph based representation of trading networks, we utilize two algorithms: PageRank and weighted/unweighted clustering coefficient.

PageRank, in its general application, finds the most authoritative webpage in a network, whereas in our case, it ranks the most influential user with the largest market manipulation tendency. The underlying assumption is that market manipulators artificially raise or depreciate NFT values by frequent interactions with its own sub accounts, misleading innocent traders. We employ a packet from networkx and also personalized PageRank so that it takes edge weight, the normalized number of transfers on the edge, into consideration. We then calculate page rank for users in each collection by filtering out inter-collection activities to support the visualization design.

Clustering coefficients measure how close a user's neighbors are from forming a clique, giving insights about whether a user is included in circular or grouped transactions. A local clustering coefficient can be assigned to each node in the graph using the formula

$$C_i = \frac{\{e_{jk} : v_j, v_k \in N_i, e_{jk} \in E\}}{k_i(k_i - 1)} \tag{1}$$

returning a value from 0 to 1 that describes the connectivity between neighbors of a node [20]. The overall clustering of the graph can be defined as the average of all local clustering coefficients. Alternatively, because there are multiple transactions between the same users, the graph can be constructed as a weighted, undirected graph, where each edge w_{ij} is weighted by the number of transactions between two users v_i and v_j. With this construction, a local weighted clustering coefficient [21] can be calculated as

$$C_i^w = \frac{1}{2s_i(k_i - 1)} \sum_{v_j, v_k \in N_i} (w_{ij} + w_{ik}), \quad s_i = \sum_{v_j \in N_i} w_{ij} \tag{2}$$

4.3 Visualization Interface

We design the following interactive collection/token centric and user centric diagrams to provide visual explanations to our algorithms, letting the user be part of the abnormality detection process.

The interactive bar chart portrays the aforementioned skewed turnover rate of fourteen of the most popular collections on OpenSea. When the user hovers over any of the bars, the five tokens in that collection with the highest skewed turnover rate appear in a tooltip. Additionally, if the user clicks on any of the bars, a collection filter is applied to the calendar heatmap and force-directed graph.

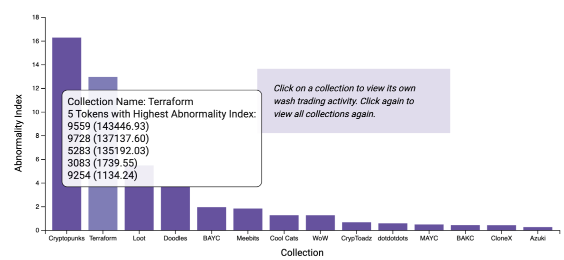

Figure 2: Collection/Token-Central Abnormality Index

The time-line heat map shows the number of tokens that have been involved in a fraudulent transaction on each day of the year, determined by the overactive token threshold. Users can adjust this threshold by dragging slider, filtering out the most suspicious tokens. Using this, we are able to track fraudulent behaviors patterns over time. For instance, the January 10th, 2022 launch of LooksRare, a platform that encourages NFT transactions in exchange for monetary rewards, can visibly be seen as a hotspot of flagged activity in the heat map. The heat map allows for greater insight into suspicious behaviors in the NFT marketplace and allows the user to identify individual instances of market manipulation within collections so that the fraud index is more intuitively understandable.

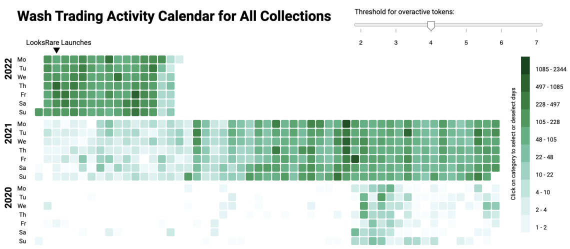

Figure 3: Time-Central Wash Trading Activity Calendar

Lastly, the force-directed diagram reveals interactions between the most influential wallet accounts. To avoid an overcomplicated diagram with an excessive number of nodes and edges, the diagram only includes top 100 wallet accounts with highest page rank. To illustrate a wallet's page rank score, the node's radius increases logarithmically as its page rank score increases. Also, the number of transfers within an edge is illustrated by the edge's changin color and width. This way, an abnormal relationship between two wallets with frequent transactions can be easily spotted. Furthermore, there is a slider that helps further remove edges with lower weights that crowd the diagram. To give a user more freedom to investigate a specific node, the visualization displays a tooltip showing a node's pagerank and clustering coefficient within the selected collection while the node is hovered over.

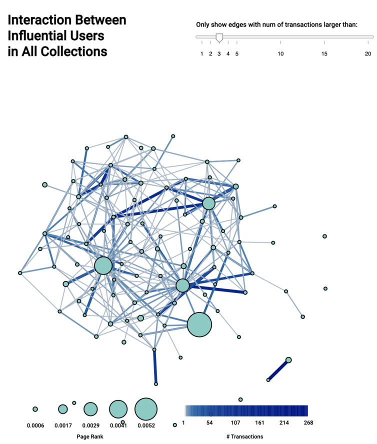

Figure 4: Interaction Network Between Influential Users

5 Experiments & Evaluation

5.1 Data Collection Analysis

Two most prevalent market manipulation behaviors in the NFT market, wash trading and pump and dump, typically feature repetitive transfers to gain platform rewards or usually fake a trading volume increase. Fig 5(a) shows the average number of transactions per token of the 10 most popular collections, with the mean appearing to be consistently around 4 and below 7. This can be explained by the fact that the NFT marketplace is still at its early stages of development and the fact that most NFT holders hold for long terms. In Fig 5(b), a small number of tokens in the Meebits Collection exhibit a number of transactions significantly higher than the average. By checking the transaction history of ten of these tokens, we found that nine of these exhibit frequent transfers between the same set of accounts. Thus, we came to the conclusion that a token's number of historical transactions is a good indicator of suspicious behavior, inspiring us to choose the fourteen most active NFT collections for analyses.

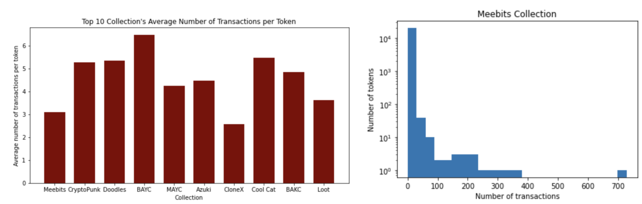

Figure 5: (a) Avg Transactions per Token (b) Meebits NFT Collection Number of Transaction Distribution

5.2 Skewed Turnover Rate Analysis

We calculate the turnover rate for 14 collections and obtain a clear and distinctive result in Figure 6. We check the trading activities on LooksRare and find that the most frequently traded tokens are in Terraform and Meebits collections, which accurately correspond to our indicator evaluations.

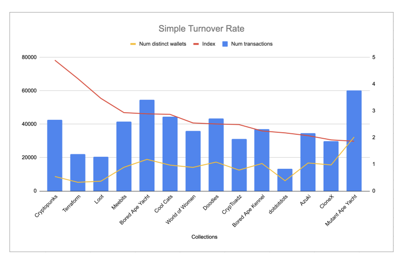

Figure 6: Simple Turnover Rate

However, we find that the novelty and activeness of a collection can affect the accuracy. For example, for the Cryptopunks collection, launched in 2017, the average turnover rate is higher simply because it is a popular collection, and its traders' average transaction times are generally higher. Therefore, in order to account for this, we introduce a normalized skewness factor measuring the distribution of customer interactions to determine if the high frequency trading is a pervasive feature or scarce abnormality. We reference Pearson's coefficient of skewness $\frac{3(\bar{x}-Mo)}{s}$, normalizing with the standard deviation of the number of transactions of each user within a collection. As showed in Figure 7(a), for normal collections, the skewness coefficient is larger because most people tend not to trade frequently, creating a positively skewed distribution. For abnormal collections with higher average numbers of trades, the skewness coefficient will be closer to zero. Combined with the turnover ratio, we get the normalized skewed turnover rate, which enlarges the gap between normal and suspicious collections in Figure 7(b).

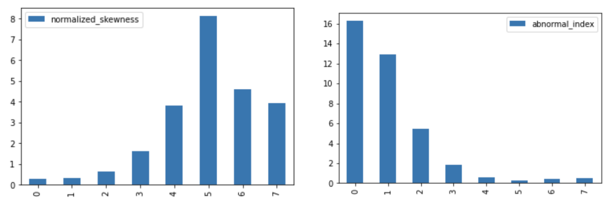

Figure 7: (a)Skewness Factor (b)Skewed Turnover Rate (both from most to least suspicious collections)

We also find that the frequency of the number of transactions per user is inversely proportional to the number of transactions, matching the Zipf's power law [22]. For the suspicious collections, such as Terraform, the frequency of even numbers of transactions for a token is usually higher than odd ones as displayed in Figure 8(a), indicating that more users are making profit from speculating instead of actually holding the object. On the other hand, for normal collections such as cloneX, the difference between even and odd number of transactions is smaller as displayed in Figure 8(b), indicating that the speculative behavior is less prevalent.

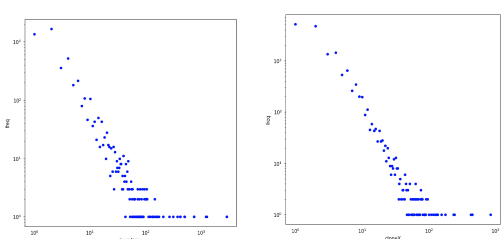

Figure 8: Frequency of Users Transactions Num (a)Suspicious Col, Terraform (b)Normal Col, CloneX

5.3 Daily Overactive Token Count Threshold Analysis

We select four typical days to define overactive. November 18th, 2021 is a normal trading day in the NFT market, and only 0.23% of all tokens are traded more than 4 times. August 29th, 2021 is an active trading day, but still, only 1.01% of tokens are traded more than 4 times. LooksRare, which promotes wash trading activities with its reward policies, was launched on January 10th 2022. We check the transaction history for that day and find a dramatic increase in the number of trades, with over 1200 abnormal transactions and 1.81% tokens being flagged as suspicious. The launch of LooksRare also increased the wash trading volume quickly and lastly. On January 12th, the total number of transactions reached 6374 with 1.29% tokens being overactive, with the largest frequency of being traded 53 times.

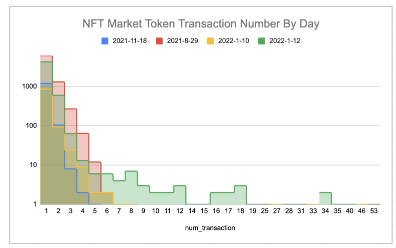

Figure 9: Comparison of Daily Trade Times of Tokens

We conclude that the launch of LooksRare successfully motivated activeness and increased the number of suspicious wash tradings, marking as an important factor for abnormality detection. We also set the default threshold for defining overactive tokens as being traded more than 4 times a day.

5.4 PageRank Analysis

After running PageRank on various subsets of our data, we get PR scores for wallets in each collection as well as for wallets in all transactions as default. In order to reveal wallet relationships that involve frequent transactions, we verified whether wallets that have frequent interaction with other accounts get a high PageRank score. In the initial examination of nodes with high PR scores, most nodes have higher degree rather than edge with high weights because the PageRank algorithm we used gives high-degree nodes higher PR scores. To customize the algorithm to give higher scores to nodes connected with high-weight edges, edge weight is squared and normalized. This change alters most nodes' PR score slightly with nodes connected with high-weight incoming edges seeing the most increase in score.

To evaluate the effectiveness of PR scores in reflecting a node's number of degrees, we checked whether large NFT collectors, who suppose to have high in-degrees, have high PR scores. The result was positive as most NFT collectors do also have a high PR score. For example, NFT collector Pranksy who has collected 3,540 NFT tokens has the third highest PR score within all wallets involved in our 14 collections.

5.5 Clustering Coefficient Analysis

The repetitive transfer scheme characterizes suspicious trading activities like wash trading or pump and dump. In unregulated, anonymous markets, it was assumed that users participating in wash trading activities (fraudsters) would form low-population, high-trade volume clusters with alternate accounts or other known wash traders. The problem becomes classifying users into two categories: fraudsters and honest participants. To determine the possible classification effectiveness of metrics such as PageRank, clustering coefficient, degree, and weighted clustering coefficient, an artificial market was simulated, with honest users trading randomly between each other, and a small population of fraudsters who traded mostly amongst their respective cliques to increase volume. The stated metrics were collected for this artificial data set to determine which ones might be a suitable classifier for real market data.

By constructing the artificial data set as a multi-directed graph, in which multiple directed connections are allowed between nodes, the best two classifiers were determined to be the PageRank and degree of each node. As is shown in Figure 10(a), the clustering coefficient and weighted clustering coefficient were not good classifiers, despite the expectation. Constructing the collected market data in a similar fashion yielded results that were much less interpretable. As shown in Figure 10(b), the data does not separate neatly into clusters as it does with artificial data.

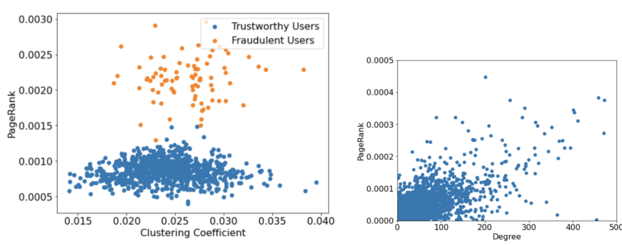

Figure 10: (a) Effective separation of fraudsters and honest users in artificial data. Note that PageRank is a more valid classifier than the clustering coefficient. (b) PageRank and degree distribution of real market data.

The results on the real dataset show that clustering coefficient would be a risky procedure in determining abnormality. After all, participants in the real market often have vastly different trading strategies, which cannot be simulated effectively with an artificial market. Also, as parameters such as trading frequency and likelihood of a wash trade are altered in the simulation, the ability to distinguish fraudulent users from honest ones in synthetic data are lost.

5.6 Result Evaluation

The elusive nature of anomalous behavior makes it difficult to validate our prediction results, so we propose four ways to make evaluations.

1) We validate our predictions with real time data on OpenSea and LooksRare manually. For example, token 9559 in Terraform has an obvious repetitive wash trading tendency with 1151 transactions in our database, and both the collection and the token are flagged as suspicious by our abnormal indicators. Besides, Visually, our heat map clearly shows the increment in abnormal market manipulations since the launching of LooksRare reward policy.

2) We cross-validate the predictions created by multiscope approaches. Our abnormal indexes serve as a reference for our exploratory network centrality analyses. Both the page rank and clustering coefficient algorithms provide distinct insights on market manipulation characteristics, and we give the power to users to evaluate whether such audacious presumptions are valuable. It is also the visualizations we create that makes the cross-validation and comparison intuitive.

3) We generate synthetic data that contains predefined anomalous behaviors in the same format as our real dataset and check if our algorithms can detect them. For example, with the synthetic dataset, the clustering coefficient seems to perform poorly, but all other algorithms and indicators worked accurately.

4) Finally, for the visualization part, we sent out a user survey containing eight questions and received over 30 responses. We improved the design by adding more illustrations explaining how to interact with the interface based on user suggestions.

6 Conclusions & Discussion

The NFT market is indeed risky with suspicious market manipulations, thus it is important to provide investors with risk assessment services to prevent obtrusive investments. Our innovative approaches proved to be intuitive and effective based on internal cross-validation, external verification with authentic sources, and user reflections. The interactive nature of our visualization also makes the software reachable and user-friendly.

In future research, we will analyze trading price differences which currently are not included from our data source but is another important factor that leads to the motivation behind market manipulation, to make profit. Also, current results inspire us to train machine learning models with the indexes we propose, such as skewed turnover rate and page rank, which diversifies the features that can be used to determine abnormality and complexity of the problem.

Our research shows that abnormality detection in the NFT market is a really promising field. With all our team members contributing a similar amount of effort, we wish to see more interest from the academic field to create a more matured and trustworthy NFT trading environment.

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