Understanding NFT Price Moves through Social Media Keywords Analysis

Junliang Luo  
McGill University  
Montréal, Québec, Canada  
junliang.luo@mail.mcgill.ca

Yongzheng Jia  
Overeality Labs  
Berkeley, California, USA  
abner@overeality.io

Xue Liu  
McGill University  
Montréal, Québec, Canada  
xueliu@cs.mcgill.ca

ABSTRACT
Non-Fungible Token (NFT) is evolving with the rise of the cryptocurrency market and the development of blockchain techniques, which leads to an emerging NFT market that has become prosperous rapidly. The overall rise procedure of the NFT market has not been well understood. To this end, we consider that social media communities evolving alongside the market growth, are worth exploring and reasoning about, as the mineable information might unveil the market behaviors. We explore the procedure from the perspective of NFT social media communities and its impact on the NFT price moves with two experiments. We perform a Granger causality test on the number of tweets and the NFT price time series and find that the number of tweets has a positive impact on (Granger-causes) the price or reversely for more than half of the 19 top authentic NFT projects but seldom copycat projects. Besides, to investigate the price moves predictability using social media features, we conduct an experiment of predicting Markov normalized NFT price (representing the direction and magnitude of price moves) given social-media-extracted word features and interpret the feature importance to find insights into the NFT communities. Our results show that social media words as the predictors result in all 19 top projects having a testing accuracy above the random baseline. Based on the feature importance analysis, we find that both general market-related words and NFT event-related words have a markedly positive contribution in predicting price moves.

1 INTRODUCTION
Non-Fungible Token (NFT), with the earliest recognized example created in 2014 by McCoy and Dash [7] registering a video clip on a blockchain, refers to a type of blockchain token that is unique and non-replicable so that it can designate the ownership of artwork, in-game items, domain names, assets in decentralized finance (DeFi), etc. [19]. The ownership is stored in a decentralized manner utilizing the emerging blockchain technique, which deters any centralized authority from owning the distinct right to remove the ownership. After the early pioneer stage, the NFT standard in Ethereum ERC721 [9] introduced in 2017 shaped the mainstream NFTs projects by standardizing NFT creation, transfer, and project deployment. The standardization is followed by an emerging NFT marketplaces to trade NFTs. NFT marketplaces have their users trading NFTs of art images, music, gaming cards, domain names, etc., for cryptocurrency. Opensea, as the largest NFT marketplace, has reached a total record of $31 billion volume and 1.8 million traders as of June 2022 [5]. The NFT trading volume as of May 2022 exceeds $37 billion, close to the total of $40 billion in 2021 [3] even though the NFT market after 2022 April has been accompanied by a starting cryptocurrency bearish market.

As the NFTs trading volume has been rising for two years, the data generated by the market began to unveil what in practice NFT contributes as an innovation. The close relation between NFTs and artwork will probably bring to mind that NFTs help encourage art creativity by making small individual artists connect with wider collectors to earn more profits. However, recent research by Vasan et al. [30] presents that despite significantly more artists joined in NFT digital art market, the artist clusters are driven by homophily, i.e., successful artists invite successful artists into the NFT market and create similar sales patterns. They highlight the forming of the artist–collector ties, i.e. some successful artists receive repeated investment from a small group of collectors. According to Nadini et al. [21], as of April 2021, the top 10% of buyers-sellers pairs contributed to the number of transactions the same as the rest 90%. These findings make us consider what NFT ecosystem builds may be pertaining to the members tie and communities.

The possession of those NFTs may have brought some private connections to the owners as well as some member benefits such as the right to receive airdrops of new related project NFTs, or to join in making decisions on the project’s funds, etc. Apart from the private connections and benefits, the project teams also build public social media communities mostly on Twitter or Discord. The community interaction about the development of the project persists to attract not just the NFT owners but every user on social media to join and engage in the communities. We consider that the rise of the prices would be witnessed by the communities formed on social media, so we intend to investigate the relationship between social media content and the NFT price moves to understand the evolving NFT market.

In our work, we collect the historical tweets and NFT trade transactions of 19 top collections ranked by Opensea in volume and 11 corresponding copycat collections (for RQ2). We conduct research for the following research questions: RQ1: Does the activeness of a social media community help in forecasting the prices and or reversely? RQ2: Will the causal relationship be inspected stronger in authentic NFT projects than the copycat projects since copycat project may not have sustained social media community building as same as the authentic projects? RQ3: Are the social media word features good predictors for the direction and magnitude of NFT price moves? More importantly, which word features mostly affect the price moves?

To answer RQ1, we perform a Granger causality test on the time series data of the number of tweets and the average trading price for each project. For RQ2, we compare the Granger causality test results of the authentic collections with the results of the copycat collections. For answering RQ3, we set up a prediction task where first we divide both tweets and transactions into segments by timeframes. We propose words vector extraction method that is based on term frequency-inverse document frequency (TF-IDF) [15] to
Table 1: NFT collections of tweets and NFT transaction data: project name, the number of assets (NFTs), contract address, Twitter account, originality, and the number of tweets and transactions.

| Project (Collection) | Assets | Contract Address | Twitter Account | Originality | Tweets (after filtering) | Transactions |
|----------------------|--------|------------------|----------------|-------------|-------------------------|--------------|
| CryptoPunks         | 10K    | 0xb47e3cd837ddf8e4c57f05d70ab865de6e193bbb @cryptopunksnfts | orig.          | 2880        | 44851                  |              |
| Bored Ape Yacht Club | 10K    | 0x838cd6b5bf716ecb1529670850b7265a2d1bbd7c @BoredApeVacancy | orig.          | 5964        | 8112                   |              |
| Art Market            | 50K    | 0x221ac9b2f91f93ba172e5f90f0f2d4a5b45ab329 @Artauction | orig.          | 4359        | 6807                   |              |
| Azuki                | 10K    | 0x07425e3e8e89e0c817b36e83c65297f6ee0a2b55 @azuki         | orig.          | 2624        | 5288                   |              |
| Clone X              | 2K     | 0x790015d4b92eab7d6f98db5edca40c26a5c85027 @CloneX         |               | 150         | 159                    |              |
| DevertoSoul           | 9.5K   | 0x660f4e36b94515f352596e3f31c46bb2d636a0d3 @DevertoSoul    | orig.          | 3459        | 14886                  |              |
| The Cool Cats        | 10K    | 0x838cd6b5bf716ecb1529670850b7265a2d1bbd7c @LilBabyCoolCats | (no acct.)     | 3459        | 14886                  |              |
| Moonbirds            | 10K    | 0x221ac9b2f91f93ba172e5f90f0f2d4a5b45ab329 @Moonbirds     | orig.          | 3596        | 8070                   |              |
| Droppendr            | 10K    | 0x221ac9b2f91f93ba172e5f90f0f2d4a5b45ab329 @Droppendr     | orig.          | 3596        | 8070                   |              |
| Noobies              | 2K     | 0x790015d4b92eab7d6f98db5edca40c26a5c85027 @Noobies       | orig.          | 1231        | 7184                   |              |
| Cool Cats            | 10K    | 0x221ac9b2f91f93ba172e5f90f0f2d4a5b45ab329 @CoolCats       | orig.          | 3596        | 8070                   |              |

extract the important words for each timeframe by treating the words in each timeframe as a document. The extracted most relevant words are likely to represent some events in each timestamp as TF-IDF emphasizes the words appear not frequently in all but in certain timeframes. We have the TF-IDF scores for each word to be used as the features along with a Markov normalized average NFT trading price to be used as the ground truth for each timeframe.

We use a simple multi-layer perceptron (MLP) regression model to perform the prediction task and analyze the feature importance to understand which features contribute to the prediction for finding the insights into the social media content. We summarize our results and contributions:

• We investigate the causality relation between the activeness of a social media community and NFT price on 19 top authentic projects and 11 copycat projects. Our results show that 11 out of 19 authentic projects show markedly Granger causality between the number of tweets and NFT price or reversely, while we find that only 2 copycat projects show Granger causality. The test results evidence the NFT price or the social media community activeness are useful in forecasting the other for an NFT project and support our hypothesis that copycat projects show weaker evidence.

• We explore the NFT price predictability given social media word features. We apply a TF-IDF-based method for retrieving the most relevant words for each timeframe to be the features and a Markov normalized average price to be the labels. Our empirical results show that 19 authentic projects have a testing accuracy above the random baseline showing a degree of predictability.

• We analyze the feature importance of the word features and find that the general market-related words and the NFT event-related words account for a notable portion of the words of most positive importance. These words contribute much more in predicting the NFT price compared to other words.

2 RELATED WORK

Recent research related to our work includes NFT market analysis and NFT market and social media studies, which will be addressed in details in the following. Other related works concern the social media text study for stock movement prediction [28], for crude oil market price prediction [8], and for global cryptocurrency price trend prediction [25].

2.1 NFT Market Analysis

NFT market has had tremendous growth in trading volume over the past two years. Nadini et al. characterized the market statistical properties such as the distribution of average price and sales per NFT from June 2017 to April 2021 [21]. They also investigated the predictability of NFT sales given the sale history and NFT price given the visual features. White et al. analyzed the sales data from OpenSea between Jan 2019 and Dec 2021 and found that a small group of whale NFT collectors are driving massive market growth [31]. Franceschet proposed a rating method for utilizing artists and collectors trading networks and evaluates the data of the SuperRare NFT market, then has some network metrics to suggest investment strategies [11].

Besides, other research discussed the potential fraudulent behaviors in the NFT emerging market, recent studies summarized malicious behaviors in NFT space [18, 26]. Das et al. performed an analysis on NFT marketplaces to discuss the security issues the NFT market is facing and one of the issues is the Counterfeit NFT creation [6]. They performed the quantitative analysis on counterfeit NFTs created by searching all NFTs in markets to find counterfeit NFT collections with similar collection names, identical image URLs, or similar images as some authentic NFTs. We note the lack of research on comparing the authentic NFT projects and the counterfeit NFT projects. To this end, we begin to study from the social media perspective, investigate the relation between social media activeness and NFT price and compare the authentic NFT projects with the counterfeit NFT projects.
2.2 NFT Market and Social Media

Before, academic work has been conducted on the interaction between social media and cryptocurrency. One such example is the social media indicator for cryptocurrency price moves prediction [23]. Besides, Phillips et al. investigated which certain topics discussed on social media are indicative of cryptocurrency price moves using a statistical Hawkes model [13] and they illustrated the results by the words that precede positive or negative return [24]. Also Mendoza-Tello et al. analyzed the impact of social media on increasing the trust to use cryptocurrencies [20]. In addition, Nizzoli et al. studied the social media manipulation patterns. They detected social media bot accounts that broadcast suspicious links and summarized the deception schemes in online cryptocurrency communities [22].

NFT is traded on cryptocurrency marketplaces and it shares a tight relation with cryptocurrency technically. NFT projects also evolve with the NFT communities emerging similar to cryptocurrency. Social media plays an essential role in NFT community development since platforms such as Twitter, Reddit, or Discord become where people know about new events for the NFT projects. Recent works showed that the social media features make improvements for an NFT valuation classification task [16]. Aside from the market, Casale-Brunet et al. analyzed the NFT communities on Twitter using social network analysis [4]. They found that most top NFTs can be considered as a single community, where most top projects are influenced by the development of the Bored Ape Yacht Club1 collection from a social network perspective. However, we note the lack of a study investigating the relationship between the language content in these communities to NFT price growth. Therefore, we seek the extension of the analysis for the impact of important words used in social media communities on NFT price moves in our work.

3 DATA COLLECTION

We collect the NFT token trade transactions for some most successful NFT collections from OpenSea top 19 (top 20 exclude marketplace Rarible) as of June 2022 and their corresponding fake or successful NFT collections from Opensea top 19 (top 20 exclude mar-

4 GRANGER CAUSALITY TEST ON TWEETS NUMBER AND NFT PRICE

Utilizing the tweets and transactions collected, we investigate the causal relationship between the social network activeness and the NFT average prices temporally, then compare the results for the original projects and copycat projects. We perform a Granger causality test given the number of tweets and the average transaction values (price of the traded NFTs) within consecutive timeframes. Granger causality refers to, given a lagged time series, the ability of the time series A to help predict another time series B from the information that time series A contains [12]. Projects that have no enough tweets to initialize the Granger causality test are removed. We set one individual timeframe to be of length 3 days. Within a timeframe, the total number of tweets and the averaged prices of the traded NFTs are calculated (with the transfer transactions filtered out) and then used for the Granger causality test.

Table 2: Squared Residuals (SSR)‐based F Granger causality test. Null Hypothesis (NH): A: The number of tweets does not Granger cause the price of NFTs. B: The price of NFTs does not Granger cause the number of tweets. Bold P‐value indicates that the null hypothesis of no Granger causality can be rejected at the 0.05 level. A midline rule separate the original and the copycat projects.

| Project (Collection) | NH | F-statistic | P-value | B | F-statistic | P-value |
|----------------------|----|-------------|---------|---|-------------|---------|
| CryptoPunks A        | 3.158 | 0.023 | 26.041 | 0.001 | 20.30 | 0.001 |
| Bored Ape Yacht Club | 6.774 | 0.007 | 7.221 | 0.003 | 5.369 | 0.001 |
| Mutant Ape Yacht Club| 1.955 | 0.269 | 2.457 | 0.138 | 1.775 | 0.137 |
| OtherNFTs for Otherside| 22.074 | 0.003 | 2.511 | 0.104 | 2.711 | 0.005 |
| Art Media Censored | 31.541 | 0.001 | 10.087 | 0.001 | 7.778 | 0.001 |
| Azuki | 0.042 | 0.937 | 0.944 | 0.396 | 0.711 | 0.399 |
| Clone X | 0.001 | 0.994 | 0.168 | 0.897 | 0.036 | 0.990 |
| Decentraland | 4.587 | 0.009 | 1.287 | 0.205 | 0.715 | 0.478 |
| The Sandbox | 2.619 | 0.113 | 2.320 | 0.112 | 2.041 | 0.123 |
| Moonbirds | 0.049 | 0.421 | 0.486 | 0.400 | 2.558 | 0.103 |
| Doobs | 0.146 | 0.706 | 0.537 | 0.575 | 0.519 | 0.017 |
| Marbels | 0.005 | 0.930 | 0.842 | 0.407 | 0.356 | 0.568 |
| Cool Cats | 0.067 | 0.822 | 0.855 | 0.442 | 2.894 | 0.060 |
| RareApe | 0.024 | 0.942 | 0.034 | 0.998 | 0.009 | 0.967 |
| CrypToadz A | 0.098 | 0.341 | 0.275 | 0.764 | 0.173 | 0.194 |
| Cryptokitties | 3.211 | 0.009 | 4.112 | 0.001 | 5.778 | 0.001 |
| Cryptoclub | 0.099 | 0.341 | 0.275 | 0.764 | 0.173 | 0.194 |
| Cryptoads | 7.205 | 0.007 | 5.756 | 0.003 | 5.856 | 0.001 |
| CryptoKitties | 3.261 | 0.009 | 4.112 | 0.001 | 5.778 | 0.001 |
| CryptoKitties | 0.099 | 0.341 | 0.275 | 0.764 | 0.173 | 0.194 |
| World of Women | 7.205 | 0.007 | 5.756 | 0.003 | 5.856 | 0.001 |
| SuperRare | 28.789 | 0.001 | 9.020 | 0.001 | 0.506 | 0.001 |
| 2.785 | 0.007 | 5.778 | 0.003 | 5.856 | 0.001 |

1https://boredapeyachtclub.com
2https://cloud.google.com/bigquery
We present the Granger causality test results in Table 2. Note that all the projects come with 2 types of null hypotheses (A and B) and 3 choices of lags (3-day, 6-day, and 9-day). As for the original projects, 11 out of 19 original projects show null hypothesis rejection and 8 show A null hypothesis rejection indicating that the number of tweets contains information that helps predict the average traded price of NFTs for those projects. Another 5 original projects show B null hypothesis meaning that the NFT price has a significant impact on the number of tweets, corresponding to the scenarios where the falling prices cause fewer tweets or the rising prices boost more tweets. By contrast, the fake or copycat projects show weak Granger causality. Only the copycat projects considered derivatives such as Lil Baby Ape Club show the number of tweets has a positive impact on the NFT prices.

5 NFT PRICE MOVES PREDICTION

After we see the evidence of the positive impact of the number of tweets on the NFT price, we then explore the content of the tweets and the features behind the content, which will potentially reveal the hidden factors that drive up the NFT prices. Our inspiration is based on the observation that the growth of an NFT project is accompanied by a series of official project events such as prior-mint promotion, release for sale, airdrop, derivative NFT announcement, DeFi or GameFi connection; and community-based events such as the interaction with influencers or celebrities, the creation of memes, the engagement of various online or offline activities. In this section, we propose a method to extract important words with importance scores from the tweets, which we use as the features to investigate the relation between these features and the NFT price moves. Then we set up a price moves prediction task given the features and perform an analysis of the results.

5.1 Event Words Extraction on Tweets

In social media communities, languages consist of a wide range of expressions about the events and the related behaviors. A method to extract the words describing the events from the tweets without prior knowledge of any events will help in building the word features. We first divide all the tweets into groups, where each group contains the tweets in a timeframe of \( n \) days (\( n \) depends on the project lifetime) so that we have a list of groups of tweets ordered by date.

We perform an NLP-based method described in Algorithm 1 to extract the features from the tweets of a timeframe, which is represented by a vector of the importance score of relevant words. We first extract all nouns and verbs for each tweet using the tool Spacy [29] with the English PartOfSpeech (POS) tagging model. After obtaining the list of nouns and verbs, we use a term frequency-inverse document frequency (TF-IDF) method to have a list of the retrieved important words and the weights of importance for the content of that timeframe. The TF-IDF method is used for measuring the importance of words, where the output is the product of TF and IDF, and a large output value of a word means the word is of high importance or relevance. TF measures how frequently a word appears in a document while IDF measures how less frequently a word appears in all the documents since the words that occur in all documents are likely to be less meaningful words such as join, like, which appear in almost all the timeframes. Here we treat

Algorithm 1 Event Words Vector Extraction

Data: Tweets in string for each timeframe

Result: Event word vector for each timeframe

```
procedure ExtractWords

for each tweet in timeframe do

    removeLinksTagsEmojis(tweet)
    removeFramesNotTransaction(tweet)
    extractWithPOS(tweet)

    for word in tweet do
        tfidf ← CalTFIDF(word, p)

    vector ← EventWordVectorize(tfidf, k)
end procedure
```

the extracted nouns and verbs from the tweets in a timeframe as a document: a document that describes the events for this timeframe.

We consider the words extracted in a timeframe can likely represent the events that happened in that timeframe. For example, in some early timeframes, mint is of a large TF, and mint will not occur with a high frequency in all timeframes. So some timeframes where the word mint occurs with a large TF-IDF are most likely to be the time when some mint events happened. We add a parameter \( p \) in line 4 and 18 in our method to be the minimum frequency for a word to be considered as being contained in a timeframe when calculating IDF. The minimum frequency is for preventing the words that are mentioned in all the timeframes but within only few timeframes frequently mentioned such as mint, from being with a small IDF score. With the minimum frequency, mint is not to be considered to occur in most of the timeframes in our method so mint will not end up with a small IDF score. IDF weights down the words that frequently appear in most timeframes such as love, cool, join, etc. A small IDF leads to a small TF-IDF output. After performing the TF-IDF method, we will make the top \( k \) TF-IDF values of words in a timeframe a vector, where the vector dimension is the union of the \( k \) words of all \( m \) timeframes: \( \sum_{\text{words}} \text{TF-IDF} \). The vectors will be used as input features for modeling the relation between events and NFT price moves.

An example of the process of the event words vector extraction is demonstrated in Figure. 1, where we use Cool Cat NFT as an example. The words extracted in those 3 timeframes, after we confirm by searching news, correspond to the events of the announcement of mint in Jun 2021, the Cool Cat meme competition in Aug 2021, and the first time cool cat floor price hits 10 ETH in Sept 2021. Nevertheless, the words are features inherently describing the events that may be unique to that timeframe. We run Algorithm. 1 on the tweets of all 19 authentic NFT collections. Table. 3 shows the overall result. The tweets for most of the collections are split into frames within a length of 2-day. For the collections launched within shorter time such as Meebits, we use a length of 1-day. Collections have been existing for a longer time such as CryptoKitties are using a timeframe length of 4-days. The lengths are considered to make the collections not have a result of too less timeframes such as 50 or too many timeframes such as 400. The number of the extracted words are with a range of 100 to more than 500. The union of all distinct words from all the 19 projects is a set of 2401 words.

We visualize the overlapping relation of the sets of the words from each project in Figure. 2 to see the proportion of the intersections for perceiving what words are shared or unique for those communities. The result shows that 0.07% words appear in all 19 projects, 3%, 4.9%, 7.7%, 31.3% of words appear in 15-18, 10-14, 6-9, 2-5 projects, 52.4% of the words appear only in one of the projects. We then observe the words that appear in most of the projects: 16 words (0.07%) that appear in all projects are check, congrat, floor, hour, keep, like, market, mint, miss, month, sale, start, team, today, use, week. These words are mostly the words used for describing the market-related or event-related content. We find the market-related or event-related content words also account for a large portion of the words appear in 15-18 projects such as volume, create, wallet, find, owner, list, hold, giveaway, own, eth, future etc. For the 52.4% of words that appear in one distinct project are more likely to be the terms used only in that community such as milk, cooltopia (name of the token and name of the community) for Cool Cats NFT, breeding, adoption (two behaviors in the game) for CryptoKitties.

Figure 2: Visualization of overlapping relationships between sets of extracted words for the NFT projects: each row represents the words (dark color sub-lines) occur in a project; columns indicate the chunks of words occur in multiple projects descending ordered from left to right by the number of projects that have this chunk of words.

Table 3: Event words extraction results for the 19 NFT collections.

| Project (Collection) | Timeframes | Length (Days) | Features (Words) | Word Mean \# Ms | Date of Data Duration |
|----------------------|------------|---------------|------------------|----------------|----------------------|
| CryptoPunks          | 191        | 2             | 564              | 2.76           | 2018-01-01 to 2022-05-31 |
| Bored Ape Yacht Club | 201        | 2             | 463              | 4.94           | 2018-04-24 to 2022-05-31 |
| Mutant Ape Yacht Club| 137        | 2             | 379              | 5.61           | 2021-08-28 to 2022-05-30 |
| Otherside             | 24         | 1             | 133              | 2.10           | 2022-05-01 to 2022-06-01 |
| Art Blocks Curated    | 267        | 2             | 510              | 5.21           | 2020-12-12 to 2022-05-31 |
| Axie                | 69          | 2             | 356              | 2.05           | 2021-02-12 to 2022-05-30 |
| CLONE X              | 83          | 2             | 200              | 2.93           | 2023-12-31 to 2022-05-31 |
| Decentraland         | 237         | 2             | 543              | 4.34           | 2019-01-24 to 2022-05-30 |
| The Sandbox           | 64          | 1             | 265              | 3.29           | 2022-01-29 to 2022-05-30 |
| Moonsharks           | 45          | 1             | 171              | 2.62           | 2022-10-14 to 2022-05-30 |
| Deadlocks            | 151         | 2             | 286              | 4.17           | 2013-11-22 to 2022-05-30 |
| Meowbits             | 65          | 1             | 349              | 1.81           | 2022-03-21 to 2022-05-30 |
| Cool Cats            | 167         | 2             | 360              | 4.63           | 2022-07-15 to 2022-05-31 |
| Bored Ape Kennel Club| 175         | 2             | 424              | 4.08           | 2022-05-19 to 2022-05-31 |
| Loot (for Adventurers)| 135       | 2             | 565              | 2.80           | 2021-08-26 to 2022-05-29 |
| CryptoKitties        | 339         | 4             | 895              | 5.78           | 2018-09-18 to 2022-05-31 |
| CrypTrade            | 152         | 2             | 340              | 3.88           | 2021-09-19 to 2022-06-01 |
| World of Women       | 152         | 2             | 333              | 4.56           | 2023-07-28 to 2022-05-31 |
| SuperRare            | 241         | 4             | 569              | 4.24           | 2019-09-12 to 2022-05-31 |
5.2 Normalized Price Regression

With the extracted words vectors as the input features, we can further investigate the predictability of NFT price moves using a simple machine learning regression model. The prediction tasks will provide understanding in terms of both the predictability of NFT price given social media information, and the question of which features contribute to the prediction positively or negatively more than other features. Since each feature represents a word with a weight value for describing events in a timeframe, we tackle to discover the insights of the relation between the language in the social media communities and the NFT price.

5.2.1 Method. The model we use is a 2-layer MLP with 64, 256 units with the last output layer of 1 unit for the regression result. We split all the timeframes of a project into 80% for training and with 3 runs of execution. The classification metrics are used since weight value for describing events in a timeframe, we tackle to movement and our regression results can be easily reformed to a previous timeframes of length 3. In the meanwhile, we use a mean of the current timeframe is 12% larger than the average price of its no previous timeframes. After the normalization, for example, with the normalization:

\[
\hat{y}_i = \frac{y_i - \bar{y}}{\text{std}(y)}
\]

\(y_i \) is the raw price at the timeframe \(i\), and the Markov normalized price \(y'_i\) will be calculated by being divided by the average of its previous \(n\) raw prices. The first \(n\) timeframes will be dropped since have no previous timeframes. After the normalization, for example, with an \(n = 3\), a normalized value of 1.12 means the average NFT price of the current timeframe is 12% larger than the average price of its previous timeframes of length 3. In the meanwhile, we use a mean absolute error (MAE) loss with a penalizer \(\delta_i\) (\(\delta_i = 1\) if the ground truth \(y_i\) and prediction \(\hat{y}_i\) are both >1 or both <1, otherwise \(\delta_i = 2\)) for wrong price moves predictions as the equation below shows.

\[
\text{loss} = \delta_i \times \frac{1}{m} \sum_{i=1}^{m} |y'_i - \hat{y}_i|
\]

5.2.2 Results. We evaluate our model using both the regression metric MAE and the classification metrics (accuracy and F1 score) with 3 runs of execution. The classification metrics are used since the metrics help in perceiving the correctness of the prediction of movement and our regression results can be easily reformed to a binary classification results by converting the prediction and the ground truth to 1 or 0 representing the price moves up or down (\(y'_i = 1\) if \(y'_i > 1\) else 0, the same for \(\hat{y}_i\)).

Table 4: Evaluation results of the Markov normalized price prediction.

| Project (Collection) | Train | Test | n | Acc | F1 | MAE |
|---------------------|-------|------|---|-----|----|-----|
| CryptoPunks         | 150   | 58   | 3 | 0.578 ± 0.027 | 0.325 ± 0.063 | 0.260 ± 0.016 |
| Bored Ape Yacht Club| 158   | 40   | 3 | 0.633 ± 0.008 | 0.644 ± 0.061 | 0.256 ± 0.014 |
| Mutant Ape Yacht Club| 107   | 27   | 3 | 0.617 ± 0.045 | 0.548 ± 0.067 | 0.178 ± 0.019 |
| Otheredeed for Otherside| 20   | 5    | 3 | 0.600 ± 0.000 | 0.167 ± 0.289 | 0.327 ± 0.100 |
| ArtBlocks Curated    | 209   | 53   | 5 | 0.603 ± 0.033 | 0.485 ± 0.056 | 0.561 ± 0.095 |
| Azuki                | 52    | 14   | 3 | 0.833 ± 0.042 | 0.739 ± 0.067 | 0.171 ± 0.011 |
| CLONE X              | 65    | 17   | 3 | 0.549 ± 0.034 | 0.296 ± 0.046 | 0.212 ± 0.048 |
| Decentraland         | 187   | 47   | 3 | 0.586 ± 0.012 | 0.442 ± 0.026 | 0.219 ± 0.008 |
| The Sandbox          | 68    | 17   | 3 | 0.529 ± 0.059 | 0.430 ± 0.031 | 0.330 ± 0.027 |
| Moonbirds            | 33    | 9    | 3 | 0.666 ± 0.111 | 0.467 ± 0.177 | 0.160 ± 0.028 |
| Doodles              | 86    | 22   | 3 | 0.696 ± 0.069 | 0.437 ± 0.155 | 0.223 ± 0.010 |
| Meebits              | 49    | 13   | 3 | 0.615 ± 0.077 | 0.703 ± 0.077 | 0.305 ± 0.099 |
| Cool Cats            | 131   | 33   | 3 | 0.606 ± 0.061 | 0.519 ± 0.075 | 0.304 ± 0.030 |
| Bored Ape Kennel Club| 136   | 34   | 3 | 0.558 ± 0.059 | 0.497 ± 0.119 | 0.211 ± 0.007 |
| Loot (for Adventurers)| 105  | 27   | 3 | 0.514 ± 0.037 | 0.432 ± 0.031 | 0.236 ± 0.008 |
| CryptoKitties        | 268   | 68   | 5 | 0.587 ± 0.060 | 0.361 ± 0.067 | 0.752 ± 0.014 |
| CrypToads            | 103   | 26   | 3 | 0.640 ± 0.011 | 0.480 ± 0.165 | 0.187 ± 0.027 |
| World of Women       | 119   | 30   | 3 | 0.733 ± 0.033 | 0.579 ± 0.100 | 0.155 ± 0.033 |
| SuperRare            | 190   | 48   | 3 | 0.576 ± 0.024 | 0.417 ± 0.049 | 0.475 ± 0.015 |

The prediction results shown in Table 4. present a better than a random baseline of .5 accuracy price moves predictive performance for all the collections. Since we use a Markov window of length 3 or 5 to confine the normalization calculated on a short period prior to the current price, the predictability reflects the words as the predictors of a relatively quick NFT price change within a week or two considering small liquidity. It is important to note that the words used for discussion on social media about the NFTs are inherently not decisive predictors for price moves, since the price change is accompanied by heterogeneous market behaviors. Nevertheless, the prediction task does help in investigating which words take an effect on price moves prediction, which will provide us more insights into the events behind the language used in NFT communities and the effect on price.

5.2.3 Analysis. We use the MDA method on the models for each collection to compute the importance of the features (words). The method calculates the importance by measuring how much the validation metric degrades when you remove one of the features. As a result, we can study the patterns shown in the words with the highest positive followed by the lowest negative importance scores. Figure 3 illustrates the results of these important features.

The positive values of importance indicate the words make positive contribute to the normalized price prediction task. Some general market-related words occupied a notable portion of the positive words for all of the projects. These general market-related words include buy, owner, floor, price, wallet, holder, market, sell, sell, money, own, offer, transaction, volume eth, flip, earn, etc. Particularly, the word owner (own) or holder pop up in the positive words of 10 of the projects. We suspect that the word owner or holder is associated with NFT whales or celebrities who bought or have been owning some NFTs mentioned in the social media or press. One example in history is: In May 2021, a big whale NFT collector “Pranksy” bought a large number of BAYCs and the news spread rapidly on social media, which led to a speedy sold out for the entire BAYC collections [27]. The influence of the whales or celebrities is inevitably
one of the most probable NFT price-rising reasons. In addition to owner, the word floor, which corresponds to the floor price, appears in the top 3 positive words for the project Clone X, Doodles, Cool Cats, and World of Women. In the meanwhile, the word eth also frequently appears, which evidences the recent research conducted mentioning the positive correlation between Ethereum price and NFT sales [1]. Besides, the general NFT community and event-related words such as mint, airdrop, avatar, pfp, derivative, roadmap, founder, member, team, project, chain, etc., also comprise a markedly proportion of positive words. The most common events of NFT such as mint, airdrop, and new DeFi announcement would happen with the social media communities having these words more frequently mentioned at a certain time than other time.

Most of the other positive words, in addition to the general market-related words and the NFT event-related words, are some unique terms in each community representing the name of a token, GameFi or DeFi product, derivative, or engagement of certain activities. For example, the word mana for Decentraland, and milk for Cool Cat are the ERC20 [10] tokens for the projects. The word garden for Azuki is the name of the community that the owner of azuki NFTs has access to for exclusive streetwear collabs and other live events, so as the word swamp is the community name for CryptToadz. For Bored Ape Yacht Club, the word banana exactly corresponds to the meaning of being extremely excited, also being a double entendre representing the engagement of all ape activities. The word Serums for Bored Ape Kennel Club is the derivative NFT collection Bored Ape Chemistry Club, which consists of 10k Mutant Serums. The word nest for Moonbirds means the activity of earning benefits by staking the Moonbirds NFT. The word vx for Sandbox is another collection named CyberKongz VX being the avatars interoperable with the Sandbox metaverse.

Now we look at the 20 least important words, which mostly come with negative scores. The words having a negative score of feature importance entail the result that the words have no better contribution to the prediction compared to a random noise replacement of those feature words. Words pertaining to pessimistic projections, concerns or issues such as scammer, delist, suit, fail, lose, afford, cancel, wait, miss, raise, drop etc. appear in negative words from half of the projects. It is important to notice that these negative words don’t mean a negative correlation between the appearance of these words and NFT prices. Instead, these words made a negative contribution to the prediction task, i.e., disturbing the predictions of NFT price. We see sometimes the market-related or event-related words, such as hit, floor, sell, founder, sale, avatar pop up in the negative words of some projects. These words nevertheless less frequently appeared in negative words than in positive words.

We also find many community distinct terms are in the negative words for some individual projects. The word meebit in CryptoPunks, Serum in Azuki, Doodle in Clone X, Azuki in Meebits are some names of other projects people mention together probably because of news such as one beat out another in price, or just people are discussing and comparing the benefits to choose one of those to purchase. Other collections people also mentioned in addition to the competitive collections are the copycat collections. For example, the punk in Moonbirds may point to MoonbirdPunks, which is a mixture of CryptoPunks and Moonbirds. Another situation is illustrated by the word vibemas in negative words of CryptToadz, is a slogan as ‘Merry vibemas’ or originally ‘vibe’ which is a trigger word in CryptToadz’s Discord for the bot to print out some turtle stickers. This word vibemas is an example of some words that may frequently pop up in a specific period, which will not benefit the prediction since the market behavior may not be correlated with sudden social media hilarity because of a holiday celebration.

After we examine which words have the most positive or negative importance on the price prediction, we inspect the distribution of these top 20 positive words and negative words throughout the

Figure 3: Mean Decrease Accuracy (MDA) feature importance on the 19 collections. Mean and variance are made from 5 repeat times of permuting a feature. Top 20 words with the largest mean importance values are followed by the 20 words with the smallest mean importance values from left to right.
network analysis will be a promising future work since some user nodes within the social network might be influencers or market makers, whose behaviors may evidence directly on price change. A different perspective rather than NFT prices is analyzing the transactions network by utilizing the social-media-extracted features to perform de-anonymization on the transaction addresses [2]. Better de-anonymization will help in detecting fraudulent activities such as the wash trade on the NFT market to address potential security concerns.

6 CONCLUSION AND FUTURE WORK

This paper contributes to exploring the relation between the NFT social media communities and the NFT price in terms of the tweets number and the content of the tweets. We first present positive results of a Granger causality test between the number of tweets and the prices time series for more than half of the authentic projects, compared to seldom Granger causality for most of the copycat projects. Later we propose an event words extraction method and a regression model for predicting a Markov normalized price given the extracted word vectors, with the results showing a certain level of predictability for the normalized price. Last we analyze the feature importance and summarize the findings of insight events behind the words and their effect on predicting the price.

Future work can take several directions. We can expend the data to other platforms such as Discord and Reddit for having more text content about the events that exist. We can combine extracting other types of information from the social media resources: performance of various platforms such as petitioners or promotioners [14]. We think the social media are more likely making a positive contribution to predicting the prices, whereas for GamFi or Metaverse projects are likely to have a starting stage of contrasting circumstances such as the building of the metaverse ecosystem environment, or guidance of the gameplay [17]. Therefore the words describing the rules are probably adding more noise in the predicting.

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