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Examining the hype behind the blockchain NFT market

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Abstract

Gartner's Technology Hype Cycle has Non-Fungible Tokens (NFTs) at the peak of the hype cycle in 2021 while not even having appeared on the hype cycle in 2020. This exploratory study looks at the spread of the hype from a social media context by examining all tweets related to #NFT. We find evidence that the communities are highly dynamic in nature which is indicative of a decentralized social movement with no strong leaders. Sentiment regarding NFTs was strongly positive across all communities with no indication of any growing negative sentiment. The community expanded at exponential rates throughout the period of study with the communities becoming more interlinked and sharing more content over time. This analysis provides a foundation on which future NFT studies, or alternative emergent technology studies could build upon.

Keywords: Non-Fungible Tokens, NFTs, Blockchain, Hype Cycle, Crypto, Social Network Analysis

Introduction

Non-Fungible Tokens (NFTs) represent digital assets such as artwork, collectibles, and in-game items stored on a blockchain. There is no doubt that the hype around NFT's exploded in late 2020 and 2021 as news stories about digital artwork selling for millions of dollars appeared in mainstream media. In this exploratory study we examine how the hype spread through social media, namely Twitter, by examining all tweets mentioning NFTs throughout this period of rapid growth.

While NFTs didn't even appear on Gartner's Hype Cycle for Blockchain, 2020 (*Hype Cycle for Blockchain Technologies, 2020*, n.d.), it was already near the top of Gartner's *Peak of Inflated Expectations* in the 2021 Hype Cycle (Litan, 2021) .

Due to the rapid rise of interest in this topic, there is not an overwhelming amount of research on this topic at this time. However, just as the topic exploded in the public interest, we expect to see a similar surge in research related to NFT. Understandably, most studies related to NFT focus on the valuation of NFTs and the study of the marketplace. This is the first study to examine the spread of the NFT hype through social media. Of particular interest are a) looking at whether this is a singular community or multiple communities b) determining the consistency of those communities over time, and c) the change in sentiment over time.

Literature Review

Valuations and sales of NFTs accelerated rapidly in the first quarter of 2021. Wang et al. (Wang et al., 2021) provide a thorough overview of the technology protocols and token standards behind NFTs. The authors also report on the rapid growth in the sales volume in the tokens, citing a 28-fold increase from 12 million in December 2020 to 340 million in February 2021. This meteoric rise in the demand for NFTs has attracted the attention of researchers seeking to examine the phenomenon from various perspectives.

Some NFT research has focused on the networks that have formed around the marketplaces. Vasan et al. (Vasan et al., 2022) focus their attention on the Foundation platform. Here, artists may list their NFTs for sale and collectors can make bids. Both parties can invite artists to join the network and the authors analyze the arising social networks of artists. They consider the Twitter footprints of the artists and how they correlate with the prices they fetch for their work. They find artists' visibility on Twitter to be a weaker predictor of their earnings than visibility on the Foundation platform itself (both quantified by followers).

Sharma et al. (Sharma et al., 2022) take a micro approach at examining artists' interactions with NFT communities. They undertake a qualitative study, interviewing 15 NFT creators from nine different countries, using thematic analysis. This analysis suggests that artists transition from an early stage to an experienced stage where they move away from learning and creating in isolation and toward creating within communities. Experienced artists leverage their participation in platforms such as Discord, Twitter, and Telegram. While artists can find support in these communities, they come with their risks and challenges. Artists must navigate posts from malicious users. These users may offer phishing NFTs or other scams in the Discord or Twitter feed of more established NFT projects.

Other researchers consider NFTs from the financial perspective. Pinto-Gutiérrez et al. (Pinto-Gutiérrez et al., 2022) collect Google search activity to determine what factors drive investor interest in NFTs. Using quantitative methods, they find that there was a strong connection between the prior week's Bitcoin value and the current week's interest in NFTs. Dowling (Dowling, 2022) examines NFT pricing in secondary markets within the Decentraland ecosystem. In their metaverse he found there to be inefficient pricing of LAND tokens. In (Ante, 2021), Ante undertakes an investigation of the 14 largest NFT submarkets. He finds that there is synergy among the success of the different NFT markets. In this same paper, he opines (as the authors ponder in (Pinto-Gutiérrez et al., 2022)) whether the huge NFT trading volume increase in early 2021 can simply be attributed to rising cryptocurrency prices.

Nadini et al. (Nadini et al., 2021), offer a comprehensive analysis of the NFT landscape, focusing on sales, prices of primary and secondary sales, and the resulting networks. They study the distribution of NFT by type (eg. Art, Games, Metaverse) over their short history and the frequency with which the different categories are traded. They also look to estimate prices using quantitative methods. They consider the "network of traders" as well as the "network of NFTs," providing visualizations of both networks.

Methodology

With the recent introduction of the version 2 Twitter application programming interface (API), academic licenses are now able to pull much larger amounts of data, up to 10M tweets per month, and are able to access the full Twitter archive greatly expanding the available Twitter history available to academics. Our process for acquiring and preparing our data is shown in Figure 1, which we will explain next.

Using the Twitter V2 APIs and the keyword search of #NFT, all tweets related to #NFT between 1/1/2018 and 9/30/2021 were pulled. Due to rate limits of the Twitter APIs the data had to be pulled over several months and in multiple segments making sure to keep each segment under the 10M tweet monthly limit. Tweet data and author data were stored in separate files due to the one-to-many relationship between tweets and authors.

Once all of the tweets were collected, the files were merged to create a single complete dataset and any duplicates were removed. This process was then repeated for the author files. We then merged the primary author data (i.e. the author information for each generated tweets regardless of whether it was an original tweet or a retweet) with the tweet data.

Our next step was to score each tweet for sentiment. Using the Vader library (Hutto & Gilbert, 2014) we scored each tweet and saved the compound score along with each tweet. Unlike other libraries, Vader uses punctuation and capitalization as influencers in the sentiment scoring, so the tweets were not cleaned in any way prior to scoring. Sentiment scores ranged from -1 (highly negative) to +1 (highly positive). In addition to capturing the score we classified each score based on the sentiment score as follows: -1 to -.5 = Strong Negative, -.5 to -.2 = Negative, -.2 to +.2 = Neutral, .2 to .5 = Positive, and .5 to 1 = Strong Positive.

Once the sentiment for each tweet was scored, we segmented our data into 5 time periods. Jan 2018 through September 2020 (Q3 2020), October 2020 through December 2020 (Q4 2020), January 2021 through March 2021 (Q1 2021), April 2021 through June 2021 (Q2 2021), and July 2021 through September 2021 (Q3 2021). The decision to combine January 2018 through September 2020 was based on monthly tweet volume which showed significant increase beginning in Q4 2020.

For each period we identified each retweet and extracted retweet information including the original author, the account that retweeted that original author, and the number of times that account retweeted the original author in that time period. The retweet information was then fed into Gephi (Bastian et al., 2009) for social network analysis. Gephi was used to generate the retweet network statistics, identify the communities of conversation (i.e. modularity class), and produce the network visualizations. To keep consistency across the 5 time periods, modularity class identification was based on the Gephi default settings. In addition, no changes to the default settings were made in generating the visualizations. The visualizations were generated using the ForceAtlas 2 layout (Jacomy et al., 2014).The communities were then merged back in with the tweets.

Since our focus is on the spread of hype through social media, we generated a retweet network for each period which included the original author, the account that retweeted that original author, and a weight based on the number of times that account retweeted the original author. This gave us a weighted, directed network for each period. Network analysis was done through Gephi (Bastian et al., 2009) to capture key network statistics for each period. Gephi was then used to identify communities (i.e. modularity class) by using retweet patterns. The community for each node was then fed back into the dataset allowing us to perform a sentiment analysis, hashtag analysis, user-mentioned analysis, and topic analysis for each community. Twitter accounts that were not part of the retweet network, which occurred only if no one retweeted any of their tweets and they did not retweet anyone else, were assigned their own unique community.

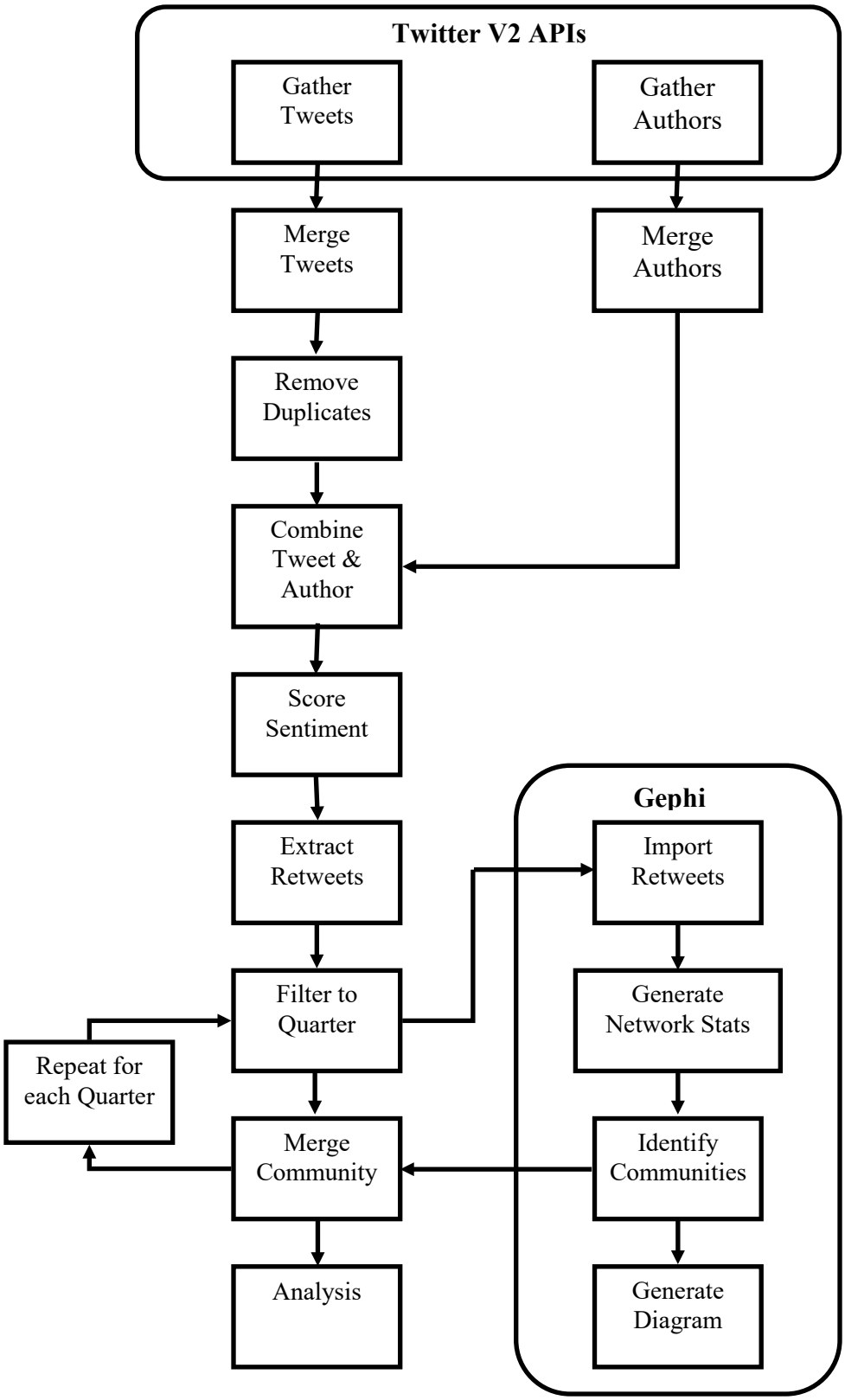

Figure 1: Data Workflow

Results and Discussion

A technology appears on Gartner's Hype Cycle beginning with an Innovation Trigger that make that technology feasible. Non-Fungible Tokens had their Innovation Trigger occur with Ethereum's ERC-721 (Entriken et al., 2018) adoption in January 2018. While there were NFTs created prior to this event, this change allowed for an easier implementation which quickly became the go-to technique for rolling out a new NFT. This standard allowed for tokens to be created with unique characteristics, frequently referred to as the token's DNA, and storing that DNA on the blockchain.

Figure 2. First #NFT Tweet

Overall, our entire dataset included approximately 27M tweets created across 1.5M unique Twitter accounts. The first tweet using the #NFT to mean Non-Fungible Token was generated by @judithESSS on Feb 12, 2018 (Figure 2). As seen in Figure 3, tweet volume increased dramatically toward the end of 2020 and throughout the entire growth period, retweets surpassed original tweets highlighting the level of sharing occurring in this community. While the innovation trigger occurred in January 2018, there is little evidence of any hype beginning until late 2020.

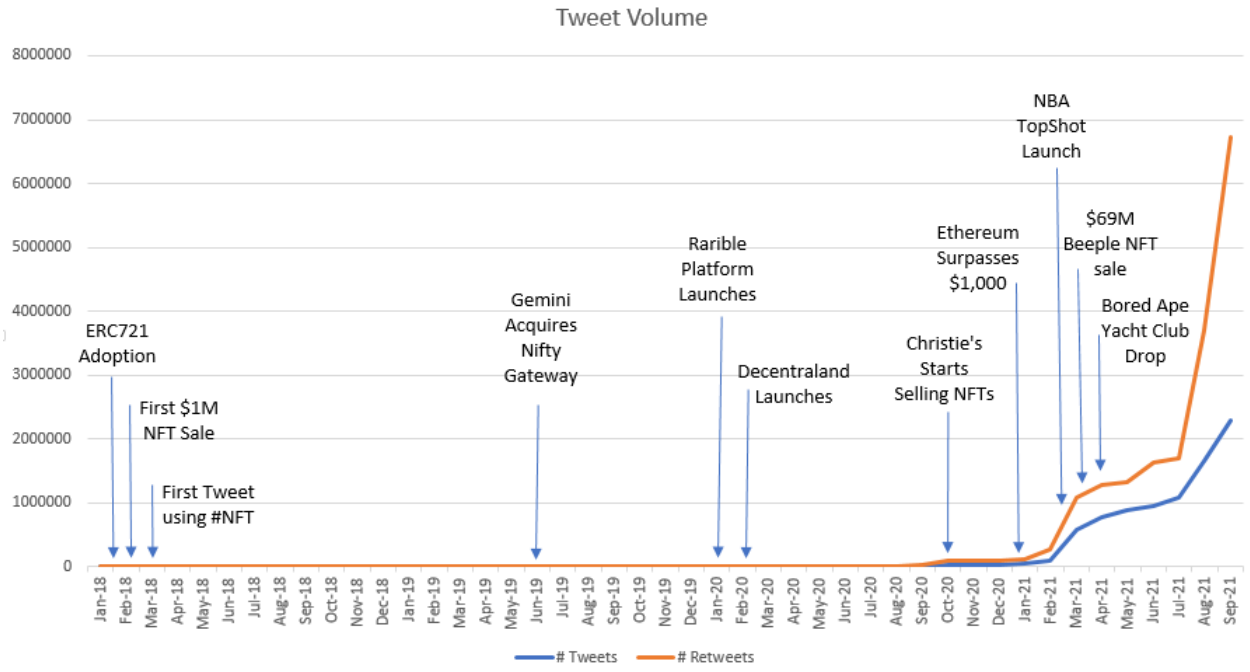

Figure 3. Tweet Volume Timeline

As mentioned in our Methodology section, the data was separated into 5 periods for analysis. General statistics per period are provided in Table 1. We see exponential growth in both tweet volume and number of accounts, quarter over quarter, with our highest growth rate, as measured by percentage growth, in Q1 2021. The average number of retweets that any given tweet has increases across the entire period suggesting

that, as the number of community members increases, the likelihood of a tweet being retweeted also increases. However, unlike the retweet feature, the number of replies, likes, and quotes do not experience the same growth, suggesting these features are not being utilized in the same manner as the retweet feature.

Table 1. Twitter Community Characteristics

	Q3 2020	Q4 2020	Q1 2021	Q2 2021	Q3 2021
Tweet Characteristics					
Total # Tweets & Retweets (growth)	272,696 (n/a)	390,025 (43%)	2,219,571 (469%)	6,833,267 (208%)	17,145,966 (151%)
Avg # Retweet	73	294	749	1,362	1,781
Avg # Replies	0.31	0.58	0.68	0.55	0.55
Avg # Likes	2.37	2.54	2.79	1.95	1.47
Avg # Quotes	0.16	0.41	0.14	0.19	0.13
Author Characteristics					
Total # Authors (growth)	43,626 (n/a)	74,688 (72%)	378,878 (407%)	843,334 (123%)	1,384,702 (64%)
Avg (max) # Author Followers	4,646 (16,895,230)	2,590 (5,007,656)	3,000 (40,773,416)	1,987 (34,687,080)	1,560 (52,791,650)
Avg (max) # Author Following	1,365 (187,351)	1,093 (379,575)	946 (4,146,518)	717 (1,435,928)	665 (1,452,416)
Avg (max) Author Tweets	14,937 (2,632,778)	10,473 (263,278)	11,702 (3,025,534)	7,549 (3,464,796)	6,802 (6,159,821)

There is evidence that celebrities jumped on the NFT band wagon early on. The most prominent figure tweeting in this space, based on the number of account followers, during our first period of study was Paris Hilton (@ParisHilton) with her 16.9M followers. Of the top 10 accounts, based on account followers, for Q3 2020, six were crypto related accounts, 3 were celebrities or sports figures, and one was a news organization. The top 10 accounts in Q4 2020, at the start of the growth period, were dominated by crypto related accounts representing 9 of the top 10 accounts, and only one celebrity in the top 10. This dynamic shifted dramatically in Q1 2021 with celebrity and sports accounts representing 5 of the top 10, news organizations representing 4 of the top ten, and a gaming platform representing the final account. In both Q2 and Q3 2021 celebrities and sports accounts represented 7 of the top 10 and news organization represented the other 3. However, only 5 of those accounts were the same from one quarter to the next. This suggests that while certain figures have been prominent long term in this space, namely Snoop Dogg and Paris Hilton, others make an appearance for a short period and then disappear.

Network Analysis

Retweets are a popular means of spreading news throughout a network. Table 2 lists the top 10 retweeted accounts for each period. Several interesting points emerge from this table. First, recall that many quarters had celebrities with huge followers participating in the conversation. None of the top celebrities appear in the table below suggesting that either a) while participating, the celebrities are not creating content that this community is sharing or b) their massive fan base is not responding to the celebrity's interest in NFTs. Second, there is only one account that appears more than once in this table, smart_nft_news. This suggests that there is uncertainty about who can claim to be strong influencers in this community. Third, this

volatility in leadership is indicative of the state of the NFT market, with NFT projects rapidly cycling between who is hot and who is not.

Table 2: Most Retweeted Accounts

	Q3 2020	Q4 2020	Q1 2021	Q2 2021	Q3 2021
1	silicanexus	smart_nft_news	phemex_official	nearprotocol	airdropstario
2	play2earncrypto	crypt0monkeys	smart_nft_news	despacedefi	borgchain
3	xcryptochild	cityalpaca	vincenttung9	cryptovenizo	ultiarena
4	phantasmaforce	dego_finance	cryptobabushka	cybermiles	cryptosanthoshg
5	0xcert	galacticnoobs	nfts_group	babyshark_fi	dvision_network
6	egamers_io	mastery_master	ecomi_	justinsuntron	roguesocietynft
7	nonfungibles	daccblockchain	jgndefi	smart_nft_news	90be90
8	thesandboxgame	nftegg	polkaventures	icoannouncement	smart_nft_news
9	eirik_the	bestswap_com	kimsenlol	hodooicom	epicheroio
10	nftpromotion	node_runners	rewardiqa	airdropdet	jamesdeannft

Retweets were used to identify the various communities that were discussing NFTs in each time period. For each retweet we identified the original author as well as the account that retweeted the tweet. If the same account retweeted that same original author more than once then a total count was used as the weight. The accounts were then used as the nodes in our network and the number of retweets became the weighted edges. The network is considered a directed network since Node 1 retweeting Node 2 is not the same as Node 2 retweeting Node 1. Network statistics (see Table 3) along with identifying the various communities were determined using Gephi.

Table 3. Network Statistics

	Q3 2020	**Q4 2020**	**Q1 2021**	**Q2 2021**	**Q3 2021**
# Retweets (% growth)	191,614 (n/a)	285,771 (49%)	1,491,431 (422%)	4,240,015 (184%)	12,125,978 (186%)
# Unique Connections/Edges (% Growth)	94,978 (n/a)	177,317 (84%)	1,010,865 (470%)	2,769,859 (174%)	8,056,709 (191%)
# Accounts/Nodes in RT Network (% Growth)	39,195	69,087	346,557	766,310	1,309,735
Average Degree	2.423	2.567	2.917	3.615	6.151
Average Weighted Degree	4.756	4.084	4.304	5.533	9.258
Network Diameter	14	16	20	19	19
Average Clustering Coefficient	.021	0.016	0.013	0.014	0.011
Average Path Length	4.663	5.724	6.362	15.902	69.527

While we were already aware of the exponential growth in tweet volume, this analysis lets us dive deeper into how retweets specifically were utilized. Again, we see exponential growth across all periods for both retweet volume, number of connections, and number of accounts. The average degree statistic tells us how many connections the average account has with other accounts while the average weighted degree tells us

how many retweets the average account makes. We see increases in both of these statistics throughout the time period indicating that throughout the growth period not only are more people joining the conversation but they are becoming interconnected more (average degree) and retweeting more (average weighted degree).

The network diameter is the maximum distance between any pair of nodes. While we see this increasing in 2020 and Q1 2021, it appears to stabilize at that point. This suggests that after Q1 2021 the size is remaining the same indicating that while many new members are joining after Q1, they are joining existing communities. The average clustering coefficient is the degree in which nodes cluster together, this value ranges from 0 (no clustering) to 1 (maximum clustering). Across all time periods we see very low levels of clustering with a general negative trend over time indicating high fluidity of movement throughout the network.

Finally, the average path length is the average number of steps along the shortest path for all possible node pairings. This is a measure of information spread efficiency. We see this increasing dramatically in quarters 2 and 3 2021. This indicates that news about any given NFT faces increasing challenges of spreading that news throughout the entire community. Next, we will turn to the network visualization for further insight.

Network Visualization

The network visualizations were created using the ForceAtlas2 algorithm as implemented in Gephi. Figures 4a through 4d represent the retweet network for each time period with the final quarter shown in Figure 5. A standard scale was used across all periods allowing us to see graphically the growth over the 5 time periods as well as compare the visualizations between periods for comparison purposes. The top 8 communities are represented by a unique color with all other communities colored gray. These top 8 communities represent anywhere from 64.8% of nodes to 77.38% of nodes depending on the quarter. The purple community is the largest community in each image with the pale green being the second largest. These two communities also appear furthest away from each other in relation to the other communities suggesting these are the two most dominant groups with the other groups being falling somewhere in between these dominant groups. By the end of Q3 2021, there are three main communities, each representing over 10% of the accounts in the network, included the purple (28.88%), green (12.96%), and blue (10.24%) communities. As you can see, these 3 communities made up over 50% of all accounts in the network.

Each Twitter account in our dataset was then assigned a community for each time period. If an account was associated with a non-top-8 community then it was reassigned to “Other”. If the account was not part of the retweet network then it was assigned “None” for that period. Once the communities were assigned we then were able to analyze all tweets (not just retweets) made by the accounts in the community. This allowed us to extract the top hashtags used in each community. In the next section we will analyze the results of the hashtag analysis.

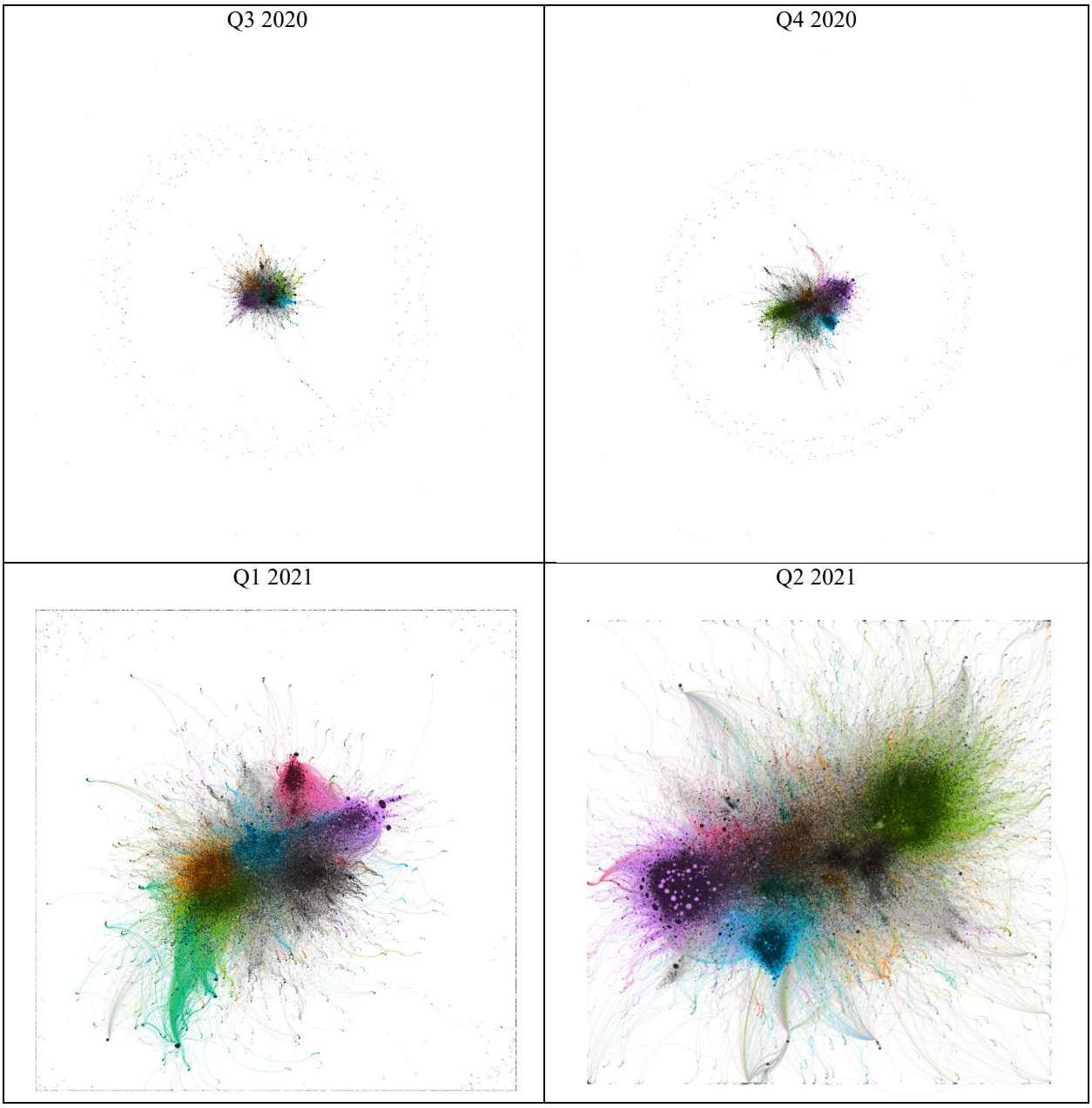

Figure 4: Network Diagrams Q3 2020 through Q2 2021

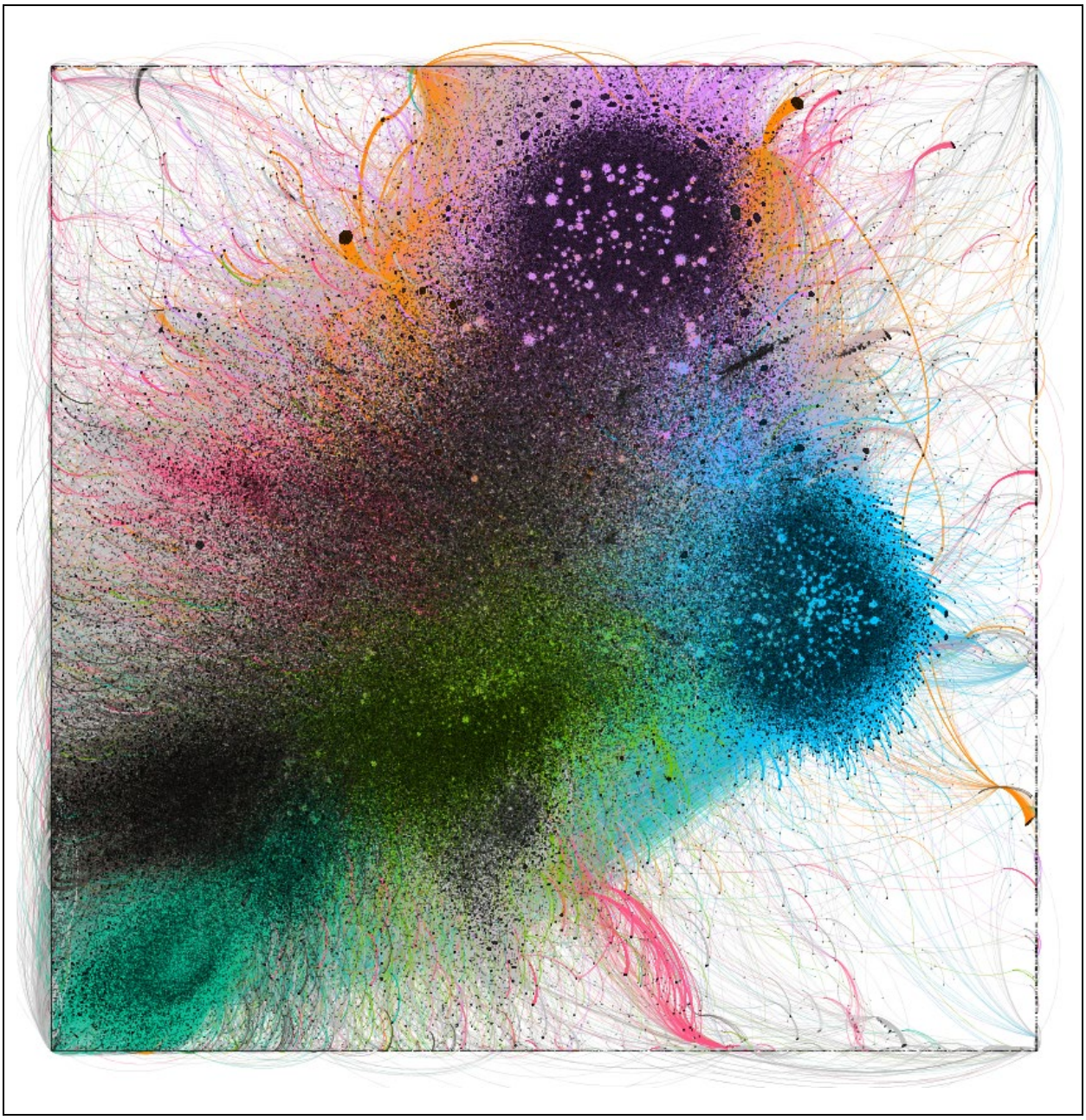

Figure 5: Network Diagram Q3 2021

Hashtag Analysis

For each of the top 8 communities in each time period we extracted the top 10 hashtags, ignoring case, used by that community, and calculated the average tweet sentiment score for those tweets mentioning those hashtags. For example, Table 4 shows the top 10 hashtags for the purple community in Q3 2021. Using the top hashtags we were able to give our communities labels. In the case of this community we gave it the label Marketplace/DeFi. We expected to use the sentiment score to help refine the definitions based on whether the community was talking positively or negatively when using that hashtag, but there wasn't a single instance where any of the top 10 hashtags had a negative average sentiment. This demonstrates that while there are sure to be those who are talking about NFTs negatively, they haven't found a common community to share those negative views, or the community is not retweeting negative views.

Table 4. Top Hashtags for Top Q3 2021 Community

Hashtag	# Occurrence	Average Sentiment
#nft	2,098,819	0.524
#airdrop	614,428	0.569
#bsc	613,011	0.486
#defi	240,323	0.509
#gamefi	230,146	0.403
#playtoearn	215,770	0.464
#giveaway	210,681	0.685
#banancesmartchain	197,517	0.465
#nfts	195,598	0.442
#crypto	151,360	0.551

Once we labeled each community, we were able to show how movement between these communities occurred over time. Community movement is shown in the Sankey chart in Figure 6. Each quarter is represented by a column of boxes that represent the top 8 communities for that period plus an additional "other" community for all the remaining communities combined. The height of each blue box represents the total number of accounts in that community in that time period. The width of each line shows the movement from one quarter to the next. So our largest community in Q2 and Q3 2021 were both labeled Marketplaces/DeFi, with a majority of accounts staying in those communities. While that one community appears to have stabilized, the chart shows us there is still significant movement between communities.

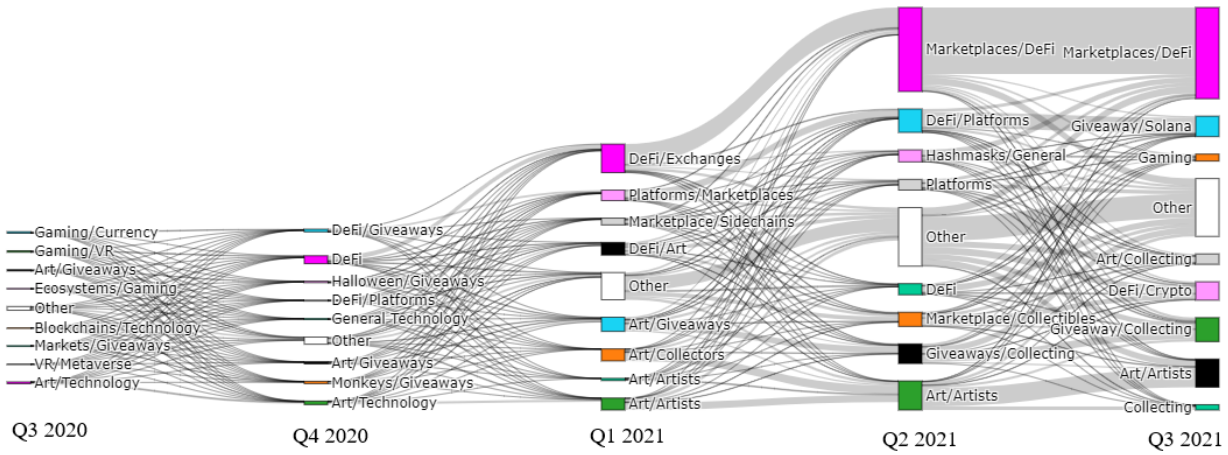

Figure 6. Community Membership by Quarter

Sentiment Analysis

Next we analyzed sentiment score by focusing in on the final three months of data, which corresponds to the highest volume period. The mean sentiment score across the 17.1M tweets of the period was .339 representing a high overall positive mean relative to other social media studies. Figure 7 shows the breakdown of the mean sentiment score by day, which shows a consistently strong positive sentiment across the three months. The trendline for this period is just slightly positive.

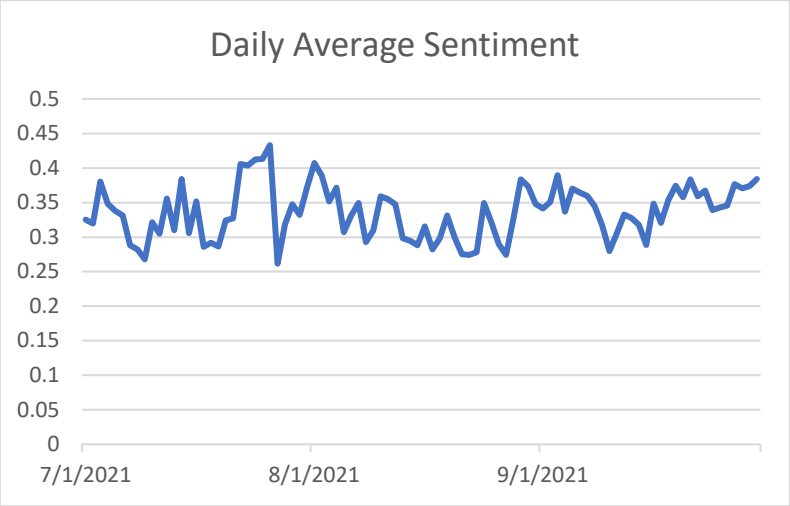

Figure 7. Daily Average Sentiment

We then analyzed the breakdown of the tweets based on the 5 sentiment classifications (High Negative through High Positive) as described in the methodology. Figure 8 shows the tweet count based on those 5 classifications. This gives us additional information including the overall volume change over the period as well as the volume by sentiment classification. We see consistent growth through early September, a slight pull back in mid-September, followed by renewed growth through the end of our study period. We see that our largest bin across the period was "High Positive" and the positive tweets appeared much more frequently than negative tweets. When viewed based on overall percentages (see Figure 9), we see that Positive and High Positive tweets represent a consistent 60% of the data while Negative and High Negative represent less than 15% of the data. In other words, there is roughly a 4 to 1 ratio of positive tweets to negative tweets and this has remained fairly consistent throughout the three months.

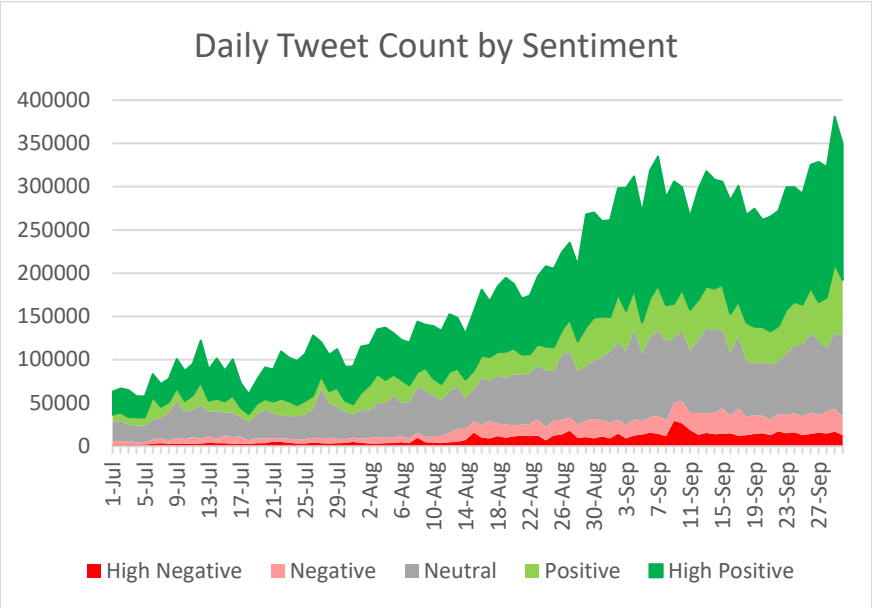

Figure 8. Daily Tweet Count by Sentiment Classification

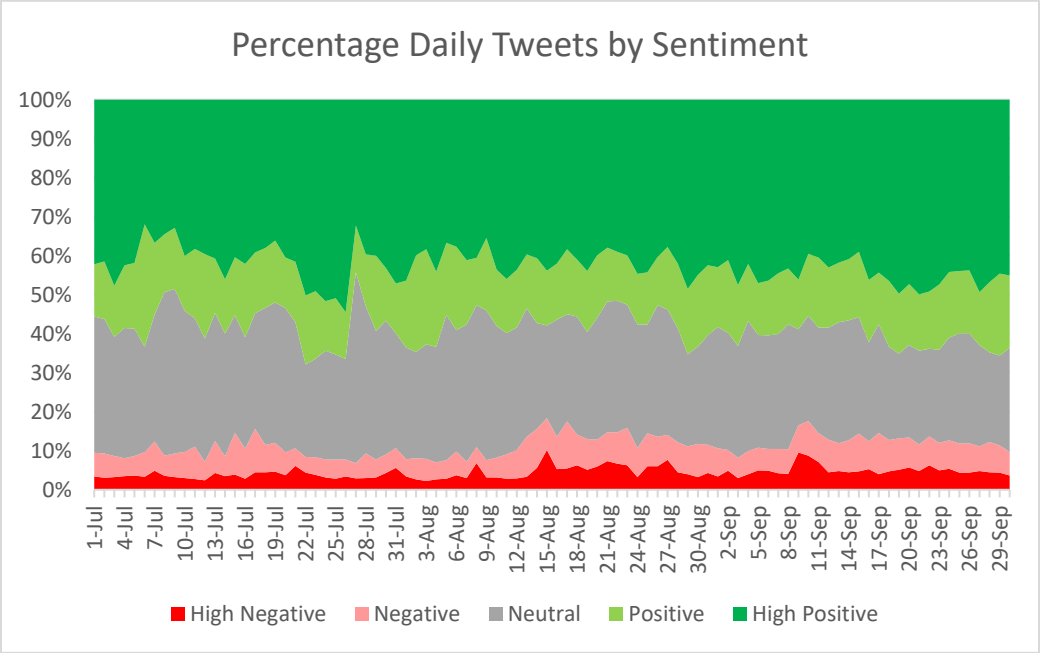

Figure 9. Percent Daily Tweet Sentiment

We were then interested to know whether there were particular communities that were more positive than others. Table 5 shows the number of tweets and mean sentiment of those tweets for the top 8 communities (corresponding to the communities in the network diagram Figure 3). All 8 communities had a positive mean sentiment score suggesting that there is not any particular large community of NFT bears. In fact, there was not a single community with more than 1000 tweets that had a negative mean sentiment. This provides further evidence that those most likely talking negatively about NFTs have not created their own community, instead they appear to be spread out across the other communities.

Table 5. Sentiment by Community

Community	Mean Sentiment	Tweet Count
Marketplaces/DeFi (purple)	0.46057	3581731
Giveaway/Collecting (light green)	0.441975	2750950
Giveaway/Solana (blue)	0.335082	2676222
Art/Artists (black)	0.193619	2024979
Gaming (orange)	0.2019	1978865
DeFi/Crypto (pink)	0.406579	475076
Collecting (dark green)	0.294727	432791
Art/Collecting (light purple)	0.327898	341453

Conclusion

Our analysis indicates that the spread of the #NFT phenomenon is indicative of a grassroots campaign. While there are celebrities involved, there is no evidence that they are driving the conversation. In fact, it still remains to be seen if any leaders will emerge who can drive this conversation. The hype exhibits massive growth, entirely decentralized, with fluid movement

across communities. If there are strong negative voices in the community, they haven't found a strong set of similar-minded folks on Twitter, as is indicated by the overall sentiment score for each community. While all communities have positive sentiment, those discussing DeFi topics are the most bullish, while communities that talk of specific artists and games are the least bullish.

Based on Gartner's hype-cycle, it is reasonable to expect a drop towards the trough of disillusionment in subsequent quarters or years.

Limitations and Future Work

For anyone participating in the #NFT conversation, you are well aware of the number of tweets that say something similar to this one (see Figure 10) which follows a common pattern: follow an account, retweet, and tag others so the word gets out, and you could win the NFT listed. We believe that a significant part of the growth of this community was done through giveaways such as this one and it represents an opportunity for future work to understand the impact these giveaways had on the growth of the market.

Figure 10. Sample Giveaway Tweet (source: https://twitter.com/edenwagmi/status/1416367714436849666)

Our analysis didn't factor in the rapid rise in crypto currency prices throughout our analysis period. It is reasonable to believe that some level of sentiment positivity that we observed was due to crypto investors who were seeing the value in their digital wallets increase during this same time.

While this paper focused on the NFT market, the same approach can be employed to study other emerging technologies. By understanding the evolution of emerging technologies through the lens of social media, future research may be able to pinpoint where a technology is on the hype-cycle based on various social media metrics such as sentiment, number of posts, and growth of participants, to name a few.

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