Analyzing and Modeling NFT Price Behavior

IEORE4523 Group Project

Fall 2021

Team Name: Stonks

Figure 1: Nyan Dogecoin NFT
Source: [1]

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Agenda:

1. Overview of NFTs
2. Data Extraction
3. Data Exploration
4. Model Description
5. Conclusion

Overview

What is an NFT?

- A Non-Fungible Token (NFT) represents a unique digital item that is stored on a blockchain [2].

  Non-fungibility separates it from a cryptocurrency [1].

  Most operate on the Ethereum (ETH) blockchain enabled by the ERC-721 standard that enables various functionalities like token transfers and ownership tracking [3].

- Smart contracts and cryptocurrency wallets facilitate transactions among market participants [3].

- Helps create an ownership structure for digital assets [2].

- NFTs can be used to represent anything digital, including art, music, in-game purchases, and tickets [1]:

Market Performance

Figure 2: The most expensive NFT ever sold
Source: [4]

On 11th March 2021, the above NFT called “EVERYDAYS: THE FIRST 5000 DAYS” sold at an auction held by Christie’s for USD 69,346,250 [5].

Market Performance

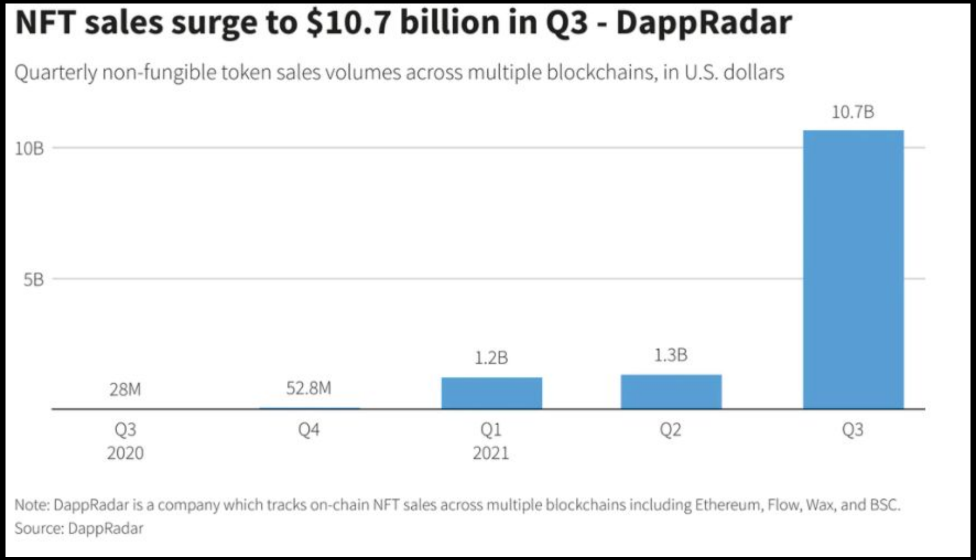

Figure 3: NFT sales surge in Q3 2021
Source: Adapted from [6]

Quarterly NFT transactions have surged 382× y/y in Q3 21…

…with significant traction in the periods after H1 21.

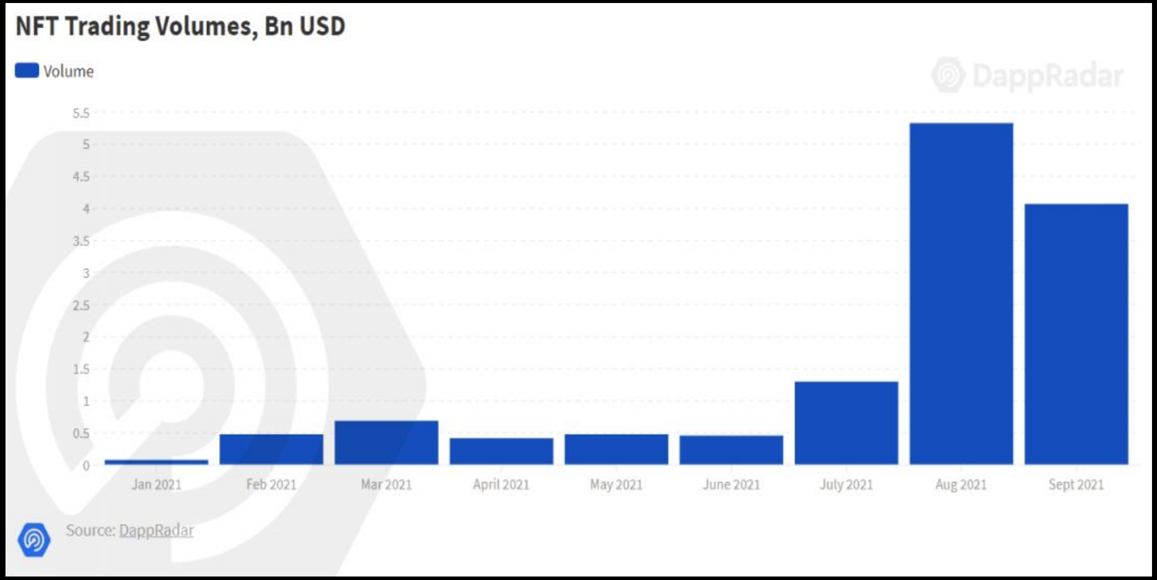

Figure 4: NFT sales volumes through Sep 2021
Source: Adapted from [7]]

Market Performance

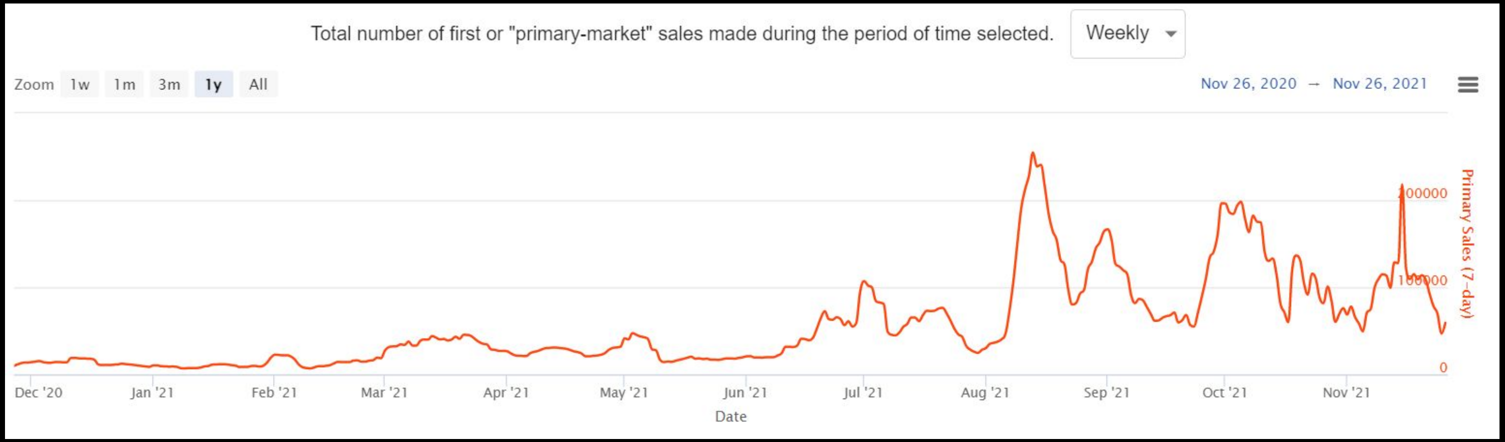

Figure 5: Weekly primary sales of NFTs
Source: Adapted from [8]

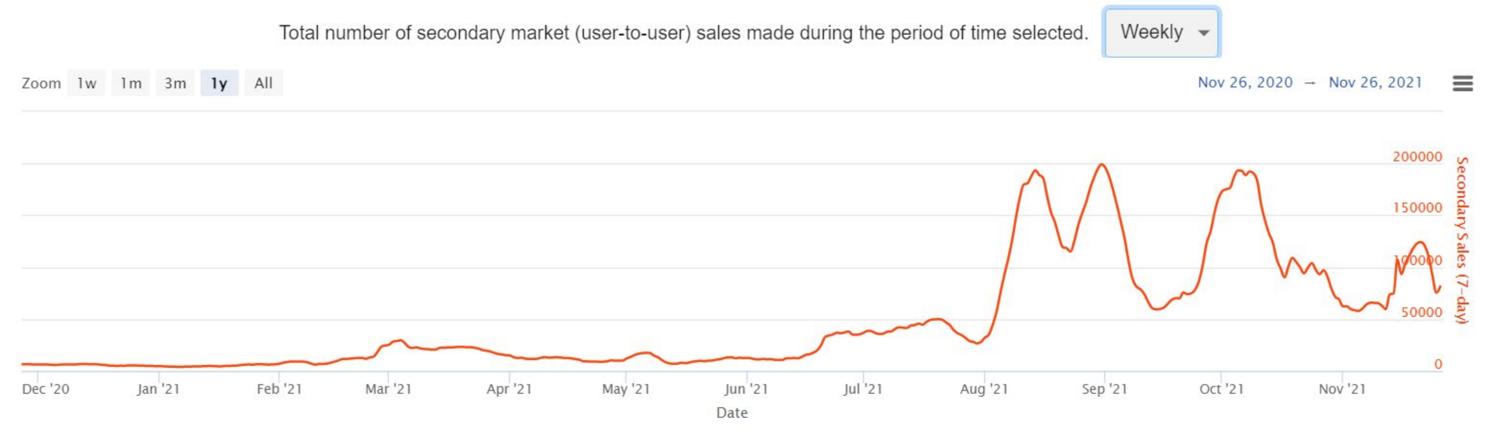

Figure 6: Weekly secondary sales of NFTs
Source: Adapted from [8]

Momentum since H1 21 is evident in the weekly token transactions on the ETH blockchain.

Market Performance

A largely inactive market has grown into mainstream popularity within a short period of time.

Figure 7: Weekly money spent on NFTs
Source: Adapted from [8]

Market Performance

Trading prices vary widely, but most tokens trade in the USD 100-1,000 range.

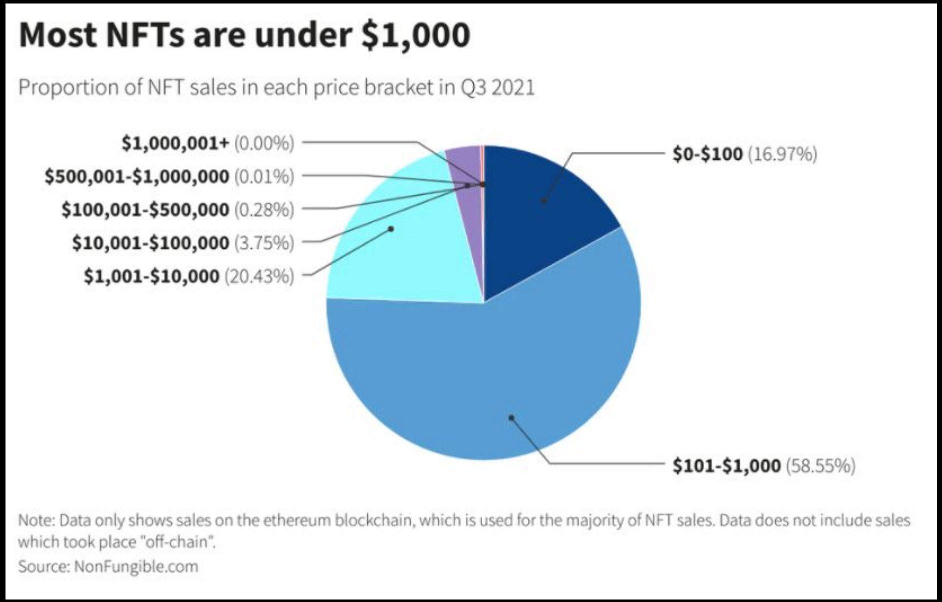

Figure 8: NFT price ranges
Source: Adapted from [6]

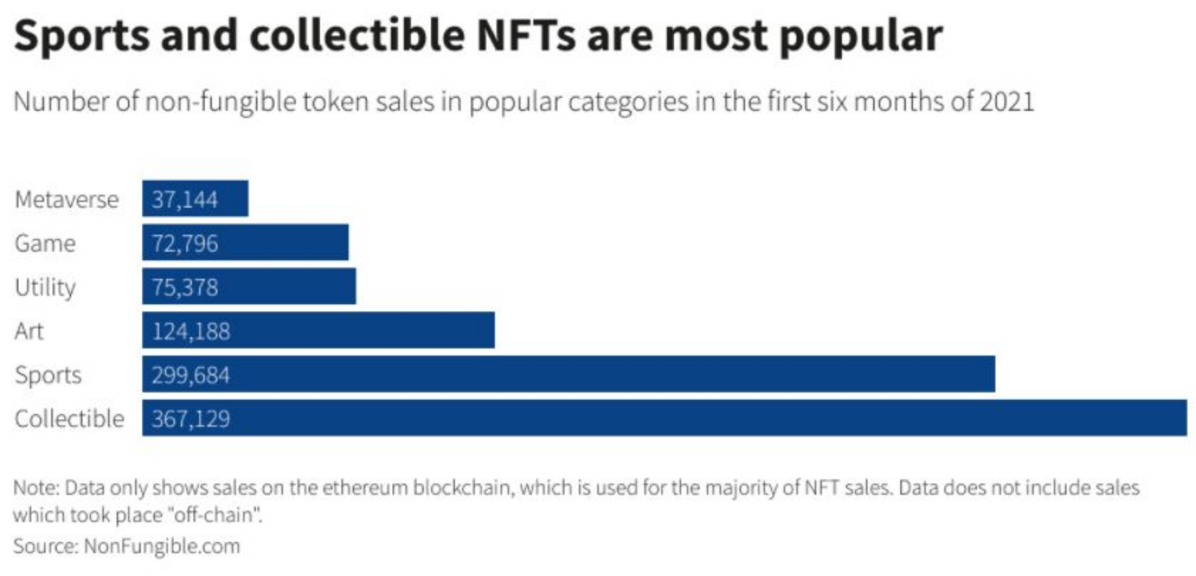

Figure 9: NFT types
Source: Adapted from [9]

Collections and sports NFTs dominate NFT trading.

Market Performance

Factors that could be attributed to rise in NFT prices and market activity:

1. Creation of a mechanism for property rights in the digital world for creative content that facilitates effective market design [2]

2. The ecosystem of services and membership benefits surrounding NFTs and its technology [2]
   - e.g. NFT may be created to give its holders access to exclusive forums/meetings/product offerings

3. Cultural significance and full ownership of commercial rights (i.e. can be used as marketing material/brand logo/profile picture without requesting explicit permission from original creator) [2]

Why CryptoPunks?

CryptoPunks represent the largest market capitalization of NFTs (both on-chain and off-chain) and rank amongst the top selling tokens each month.

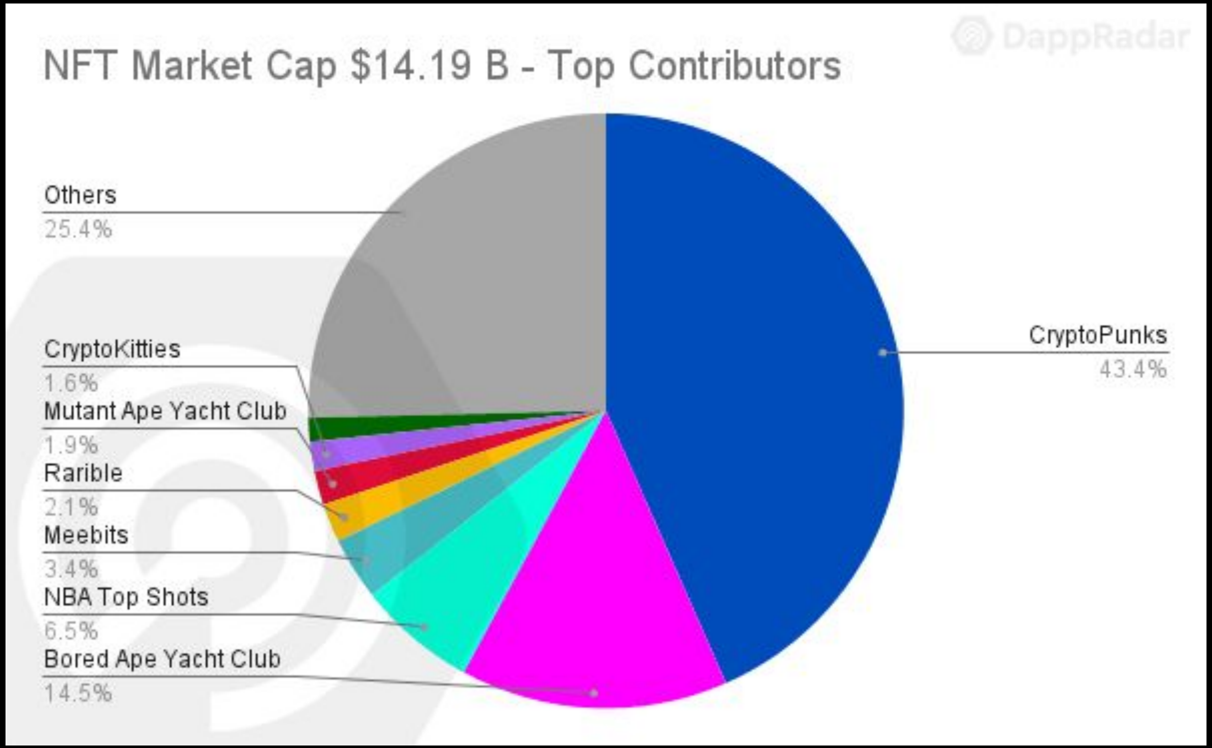

Figure 10: NFT Market Capitalization
Source: Adapted from [7]

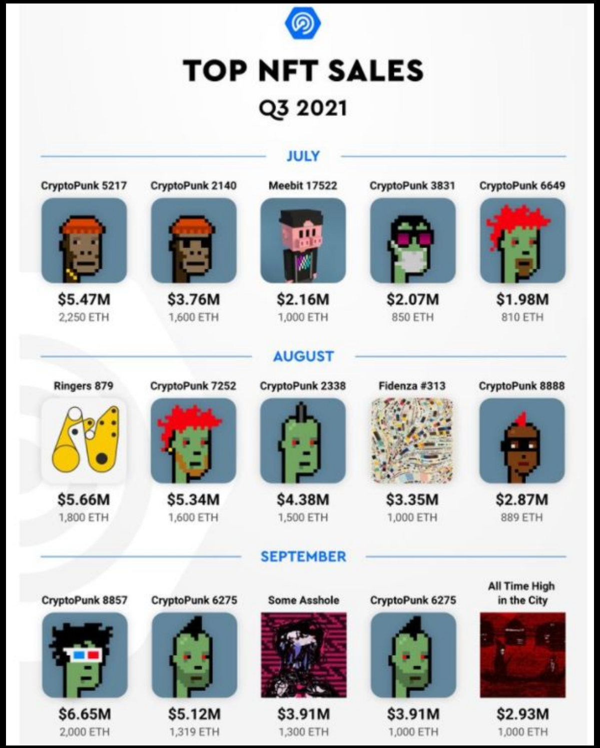

Figure 11: Top NFT sales Q3 2021
Source: Adapted from [7]

Why OpenSea?

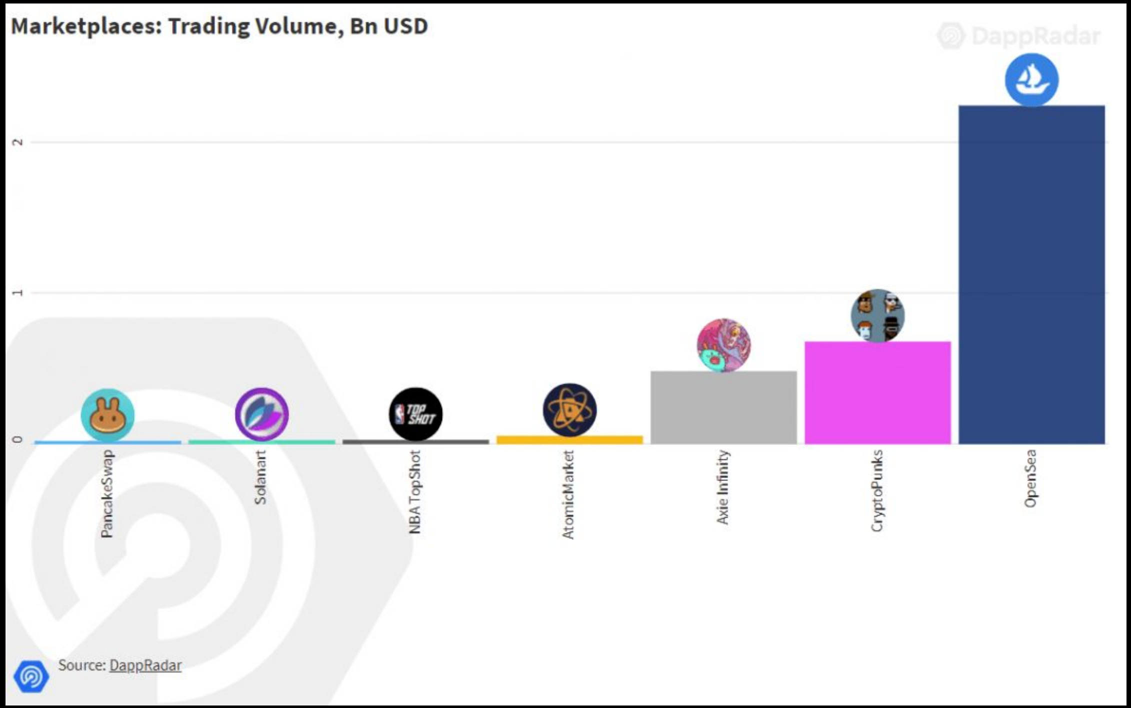

Figure 12: NFT Market Capitalization
Source: Adapted from [7]

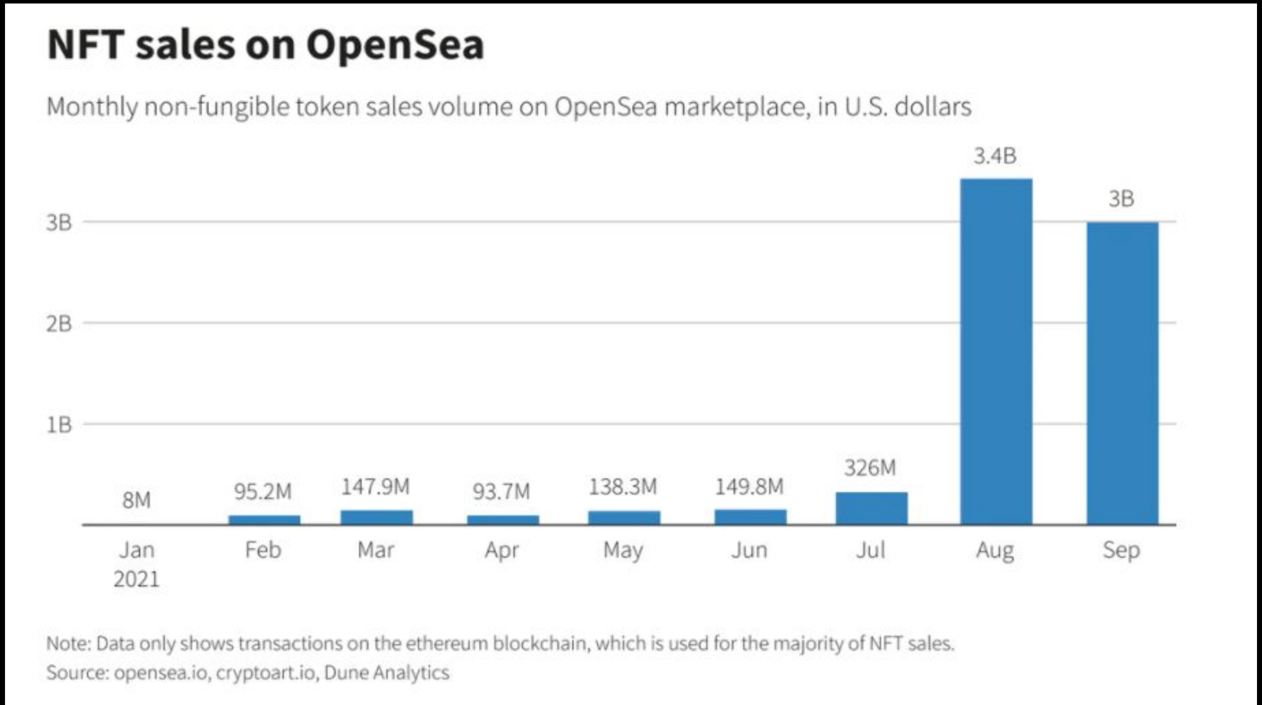

Figure 13: OpenSea NFT sales volumes through Sep 2021
Source: Adapted from [6]

OpenSea is the largest marketplace for NFT transactions that occur on the ETH blockchain.

Their volumes have also grown exponentially in the periods following H1 21 in line with the overall market.

Project Goal: Can we predict the price of an NFT based on its attributes and historical transactions?

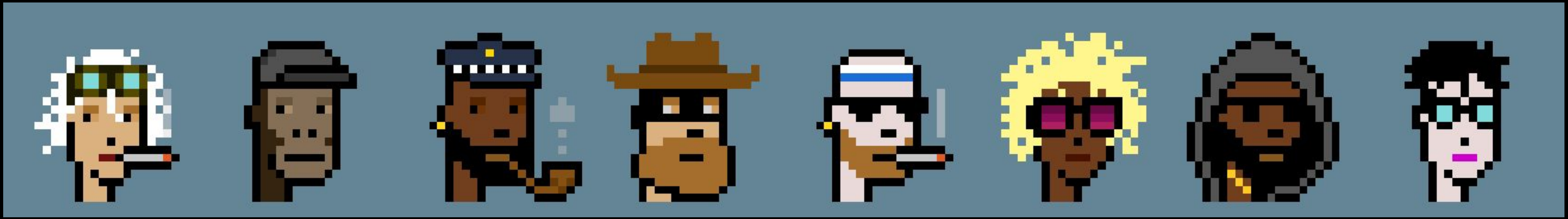

Figure 14: Ensemble of CryptoPunks NFTs
Source: Adapted from [10]

Data Extraction

Data Sources & Summary of our data

- **Data source**: OpenSea, Yahoo Finance, Twitter

- **Interface**: OpenSea API, pandas_datareader, snscrape

- **Data Set**: CryptoPunks NFT collection (10,000 tokens)

- **Types of Data:**
  1. Asset Data: *Snapshot attribute data for each token (e.g., property)*
  2. Event Data: *Historical data (from 2017 to 2021) for each token (e.g., sale price, bid amount)*
  3. FX Data: *Historical exchange rates between ETH and USD*

- **Challenges:**
  1. OpenSea took 2 weeks to approve our request for an API Key
  2. Extracting data via OpenSea API was time consuming (~1 day)
  3. API limitation: limited query frequency
  4. API failed when we tried to extract data for other NFT collections

Asset Data

id	token_id	trait_type	trait_value	trait_count
176533	0	type	Female	3840
176533	0	accessory	Green Eye Shadow	271
176533	0	accessory	Earring	2459
176533	0	accessory	Blonde Bob	147
158831	1	type	Male	6039

Figure 15: Asset data obtained through OpenSea API

- Each token is randomly generated and has unique properties with relative rarity. For example, token 0 has 'Blonde Bob' accessory that 1% of all tokens have, which indicates this property is relatively rare.
- token 0 has 4 properties out of 92.
- Rarity is not available from API, but it can be calculated based on 'trait_count.'

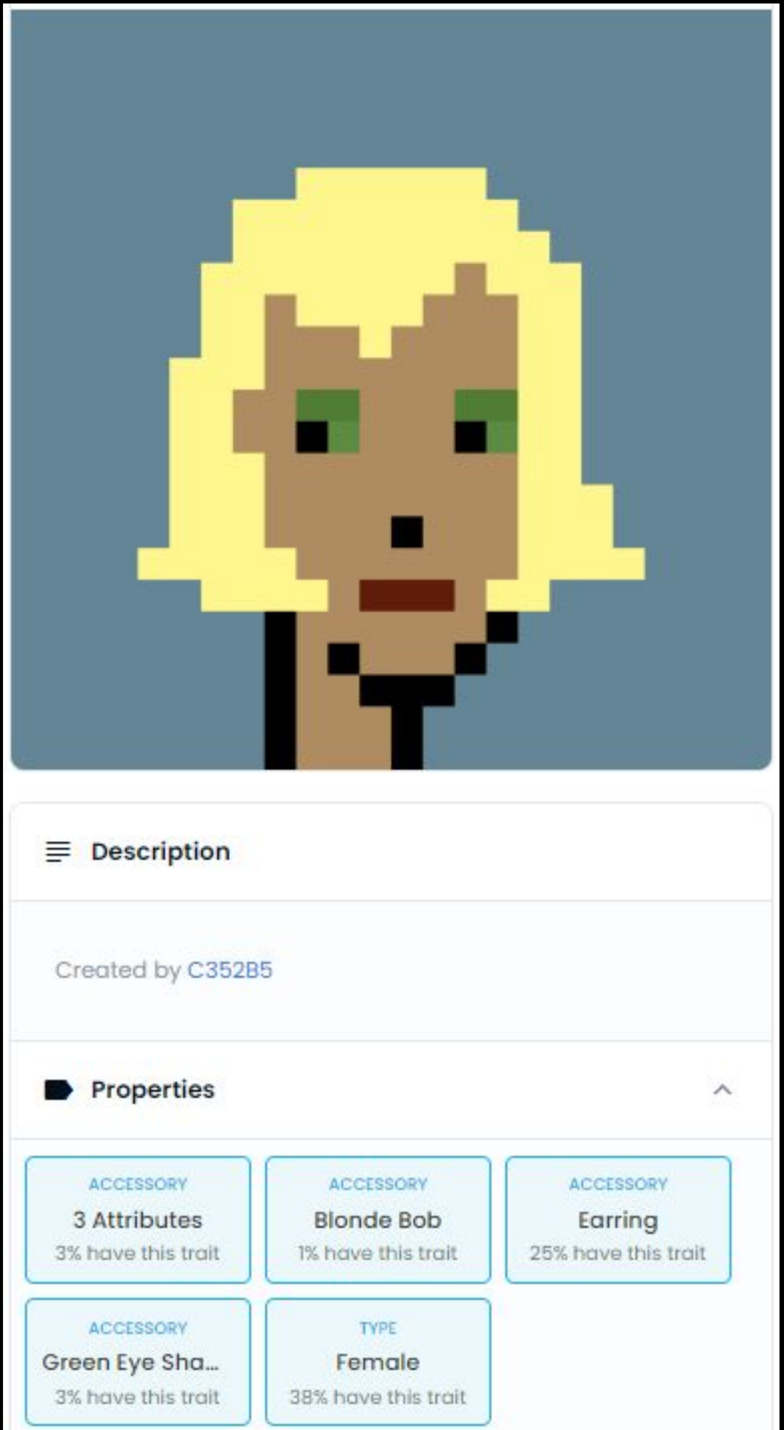

Figure 16: Data for CryptoPunk 0
Source: Adapted from [11]

Event Data

id	token_id	event_timestamp	event_type	bid_amount	starting_price	ending_price	total_price
176533	0	2021-09-04T04:40:52	bid_withdrawn	321000000000000000000	None	None	None
176533	0	2021-09-01T09:08:35	bid_entered	321000000000000000000	None	None	None

Figure 17: Event data through OpenSea API

Type	From	To	Amount	Txn
Bid Withdrawn	0xe73a1d		321Ξ ($1.26M)	Sep 04, 2021
Bid	0xe73a1d		321Ξ ($1.14M)	Sep 01, 2021

Figure 18: Price data for token 0
Source: Adapted from [12]

- Price data (in ETH) from API is 10^18 times bigger than actual price, which requires data cleansing.
- API doesn't return historical ETH/USD rates, so another source (i.e., Yahoo Finance) was used to convert it to USD amount.

Data Exploration

What makes a Cryptopunk?

- 3 Characteristics: Type, Accessory, Number of Attributes/Accessories.

trait_value	trait_count
Alien	9
Ape	24
Female	3840
Male	6039
Zombie	88

Figure 19: Types of CryptoPunks

trait_value	trait_count
Earring	2459
Cigarette	961
Hot Lipstick	696
Purple Lipstick	655
Mole	644
...	...
Orange Side	68
Tiara	55
Pilot Helmet	54
Choker	48
Beanie	44

87 rows × 1 columns

Figure 20: Attributes (excluding type) of CryptoPunks

trait_value	trait_count
0	8
1	333
2	3560
3	4501
4	1420
5	166
6	11
7	1

Figure 21: Number of CryptoPunks corresponding to different levels of attributes

How is the Rarity of an NFT Determined?

- NFT Score = SUM(1 / [Number of Tokens with Trait / Total Number of Trait Type in Collection]) [13]

- Higher Score implies more Rarity

- e.g.

	id	token_id	trait_type	trait_value	trait_count	total_trait_count	rarity	score
5217	178333	5217	type	Ape	24	10000.0	0.002400	416.666667
23701	178333	5217	accessory	Gold Chain	169	27539.0	0.006137	162.952663
23702	178333	5217	accessory	Knitted Cap	419	27539.0	0.015215	65.725537
43966	178333	5217	num_attributes	2	3560	10000.0	0.356000	2.808989

Figure 22: Score calculation for CryptoPunk 5217

Figure 23: CryptoPunk 5217
Source: Adapted from [13]

Score for token #5217: 648

Token Score Distribution

- We can note that the distribution of scores is centered around 250, with a few tokens having very high scores (rare tokens).

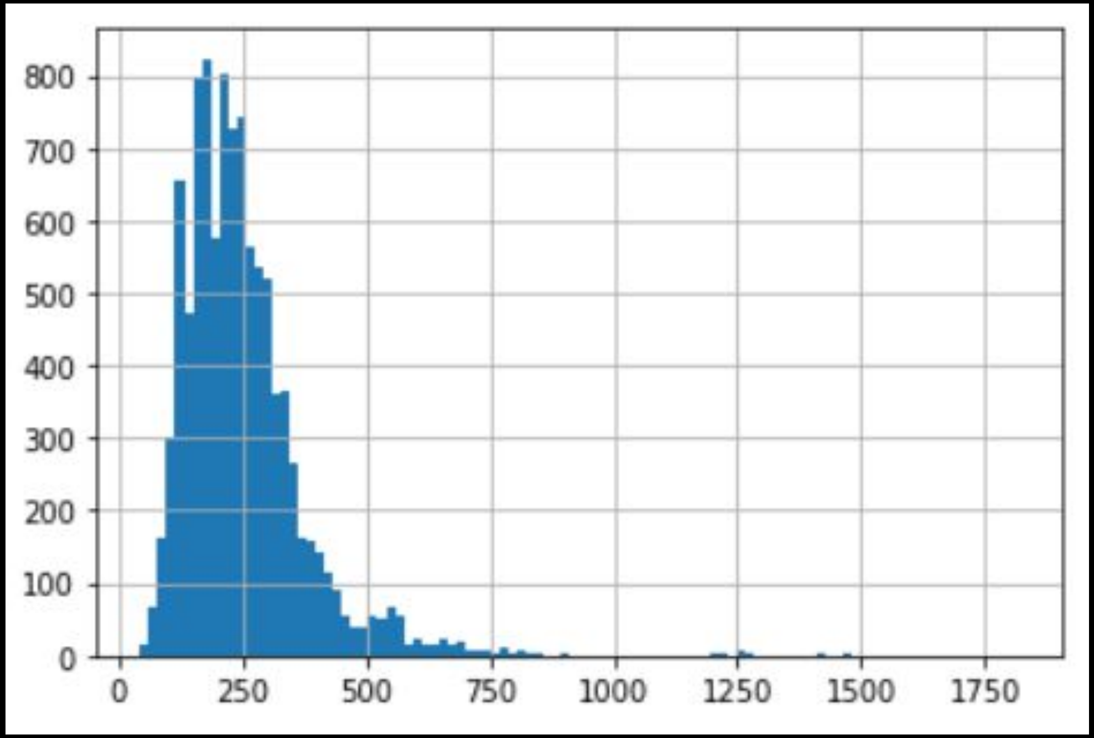

Figure 24: Distribution of tokens scores (rarity)

Data Cleansing

- Main problem in the data: Missing Transaction Data.

- Solutions:

  1. Use only observations with successful transactions.

  2. For those observations without successful transactions use max_bid and/or min_ask as a lower/upper bound proxy for the price.
     The benefit is that we increase significantly the number of observations.
     The cost is that the assumed price is less informative than the price of a successful transaction.

Data Cleansing

- Outliers: Excluded artificially inflated prices (e.g. #9998).

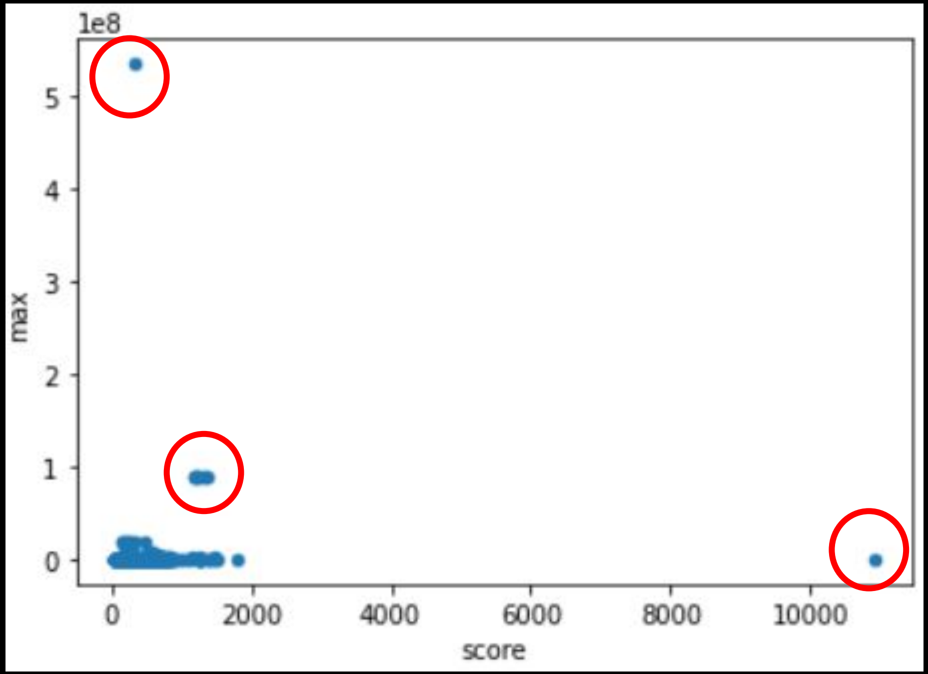

Figure 25: Max price of a token by score, including outliers

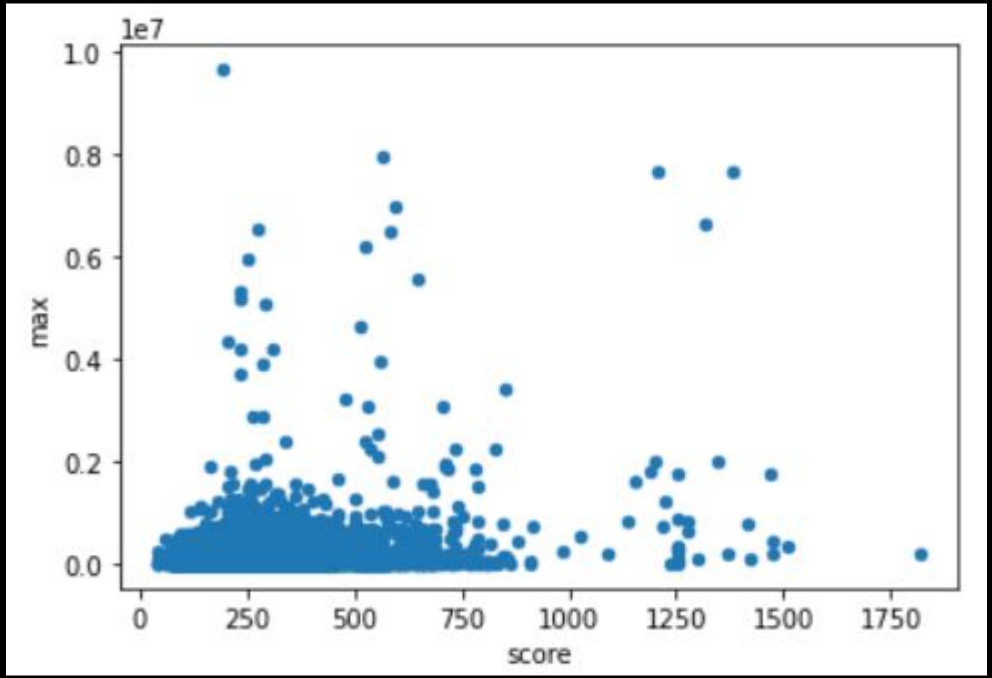

Figure 26: Max price of a token by score, excluding outliers

Value of Attributes and Types

- Top 10 by Max Price and Top 10 by Max Score

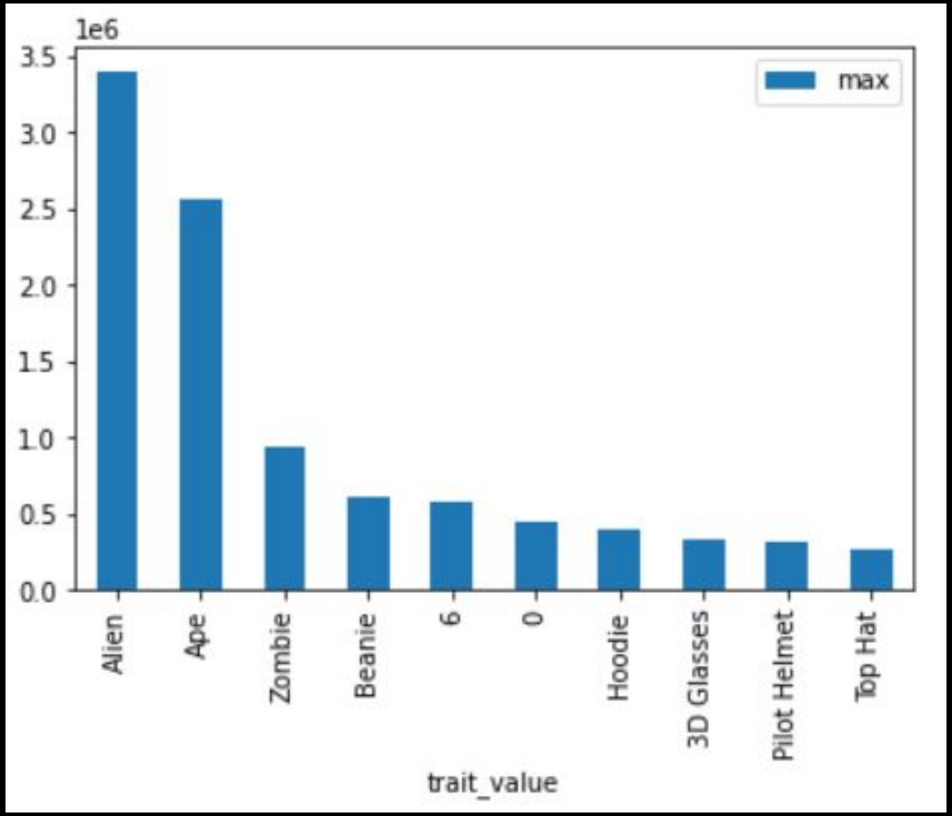

Figure 27: Top 10 most valued attributes

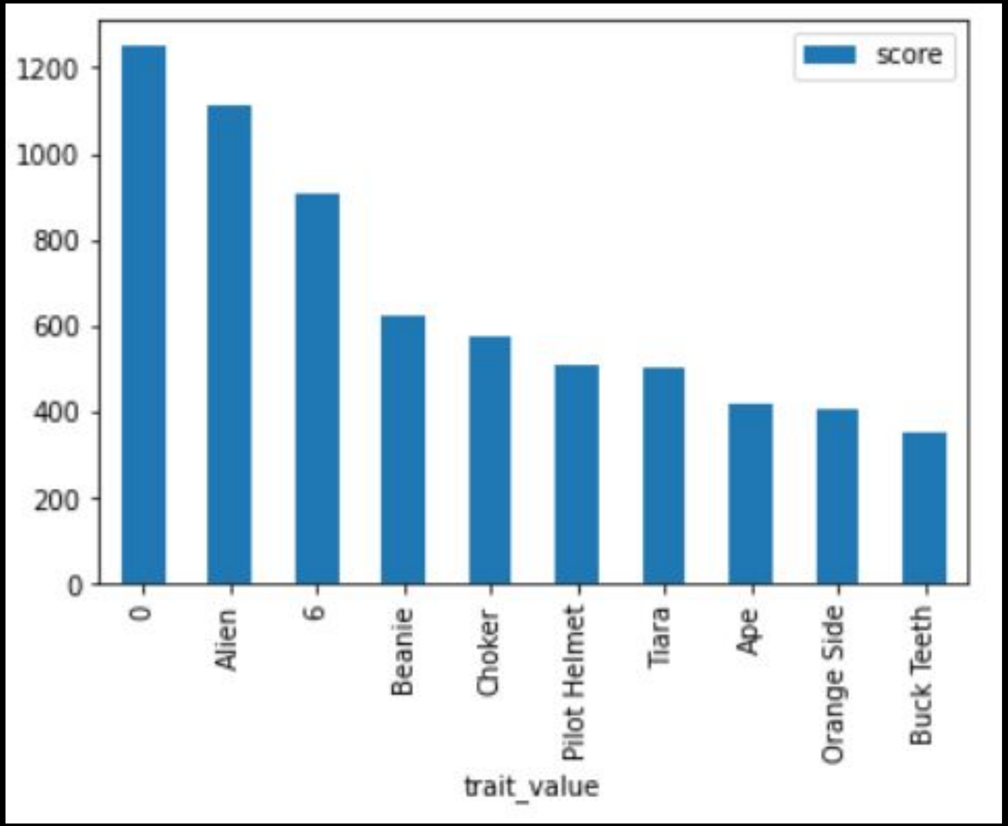

Figure 28: Top 10 attributes by rarity

Value of Attribute Score to Predict Price?

- Regression models may be ineffective due to weak relationships between score and price.

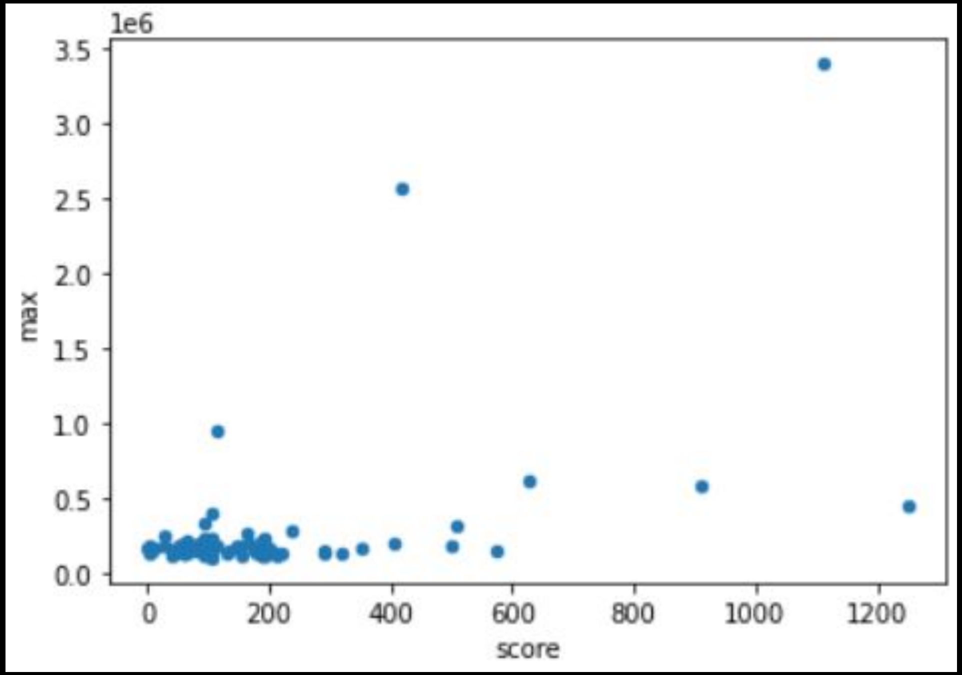

Figure 29: Score of attribute vs max transaction price of an attribute

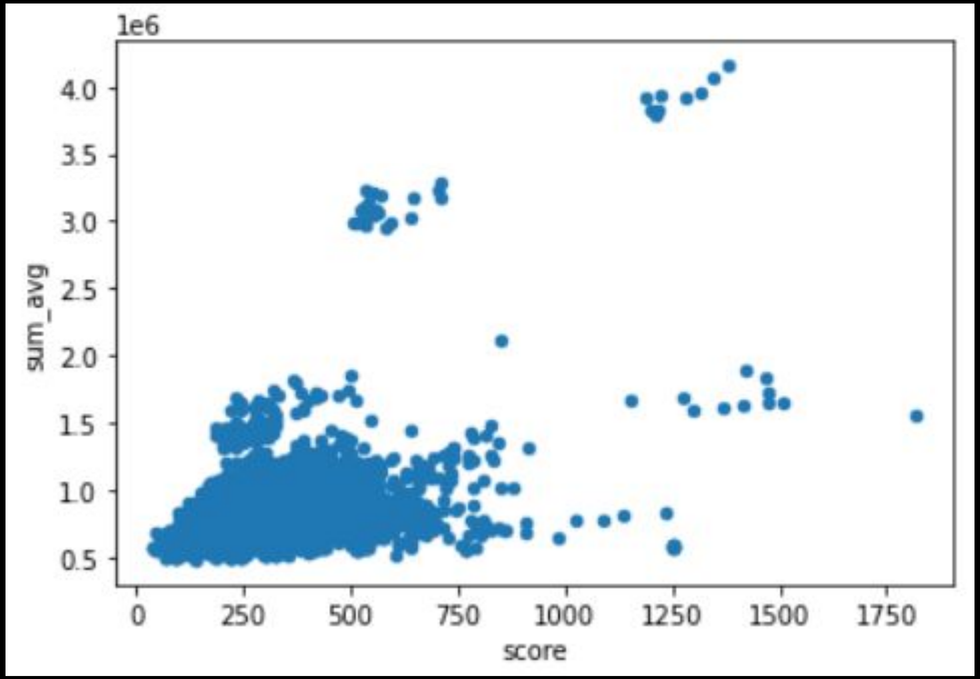

Figure 30: Score of token vs sum of average of the attribute prices that the token has

Checking ETH prices against Twitter Sentiment

- Used the snscrape library to gather 100 tweets on “CryptoPunks” for each historical date when a sales event had occurred, which were then fed into vaderSentiment
- Challenge: Had to limit to 910 data points as scraping the data was time intensive

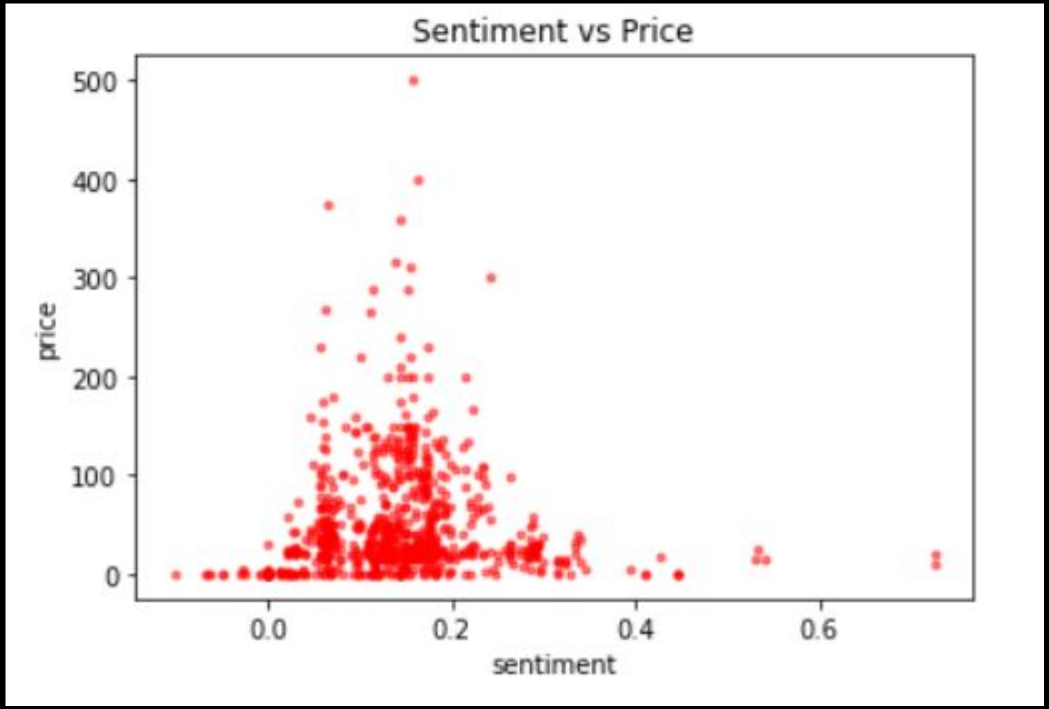

Figure 31: Twitter sentiment compared against ETH prices

Model Description

Why K-means?

- Wanted the algorithm to differentiate tokens based on rarity and inherent value.
- Group similar tokens together based on their attributes.
- Ideal result: tokens with rarer attributes will be in the same cluster. Thus, the score and price of that cluster will be higher than average.

K-Means with One-hot Encoding - Data Setup

- Sparse. The majority of the data is 0.

	1	2	3	4	5	6	7	3D Glasses	Alien	Ape	...	Tiara	Top Hat	VR	Vampire Hair	Vape	Welding Goggles	Wild Blonde	Wild Hair	Wild White Hair	Zombie
token_id																					
0	0	0	1	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	0	1	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
10	0	1	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
100	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1000	0	0	1	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9995	0	1	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
9996	0	0	0	1	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
9997	0	1	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	1
9998	0	0	1	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1	0
9999	0	1	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

10000 rows × 99 columns

Figure 32: One-hot encoding of CryptoPunks NFT attributes

K-Means with One-hot Encoding - Results

- Tried to find the optimal number of clusters (k) by finding the first big decrease in model inertia (elbow method).
- Did not get expected result with each cluster having greater differences in average scores.

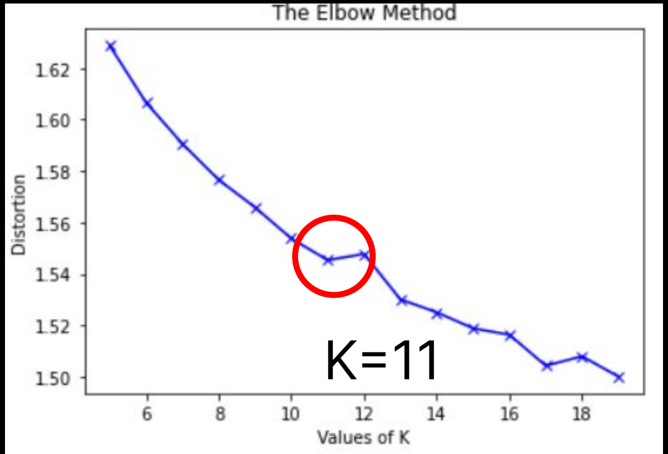

Figure 33: Elbow Method

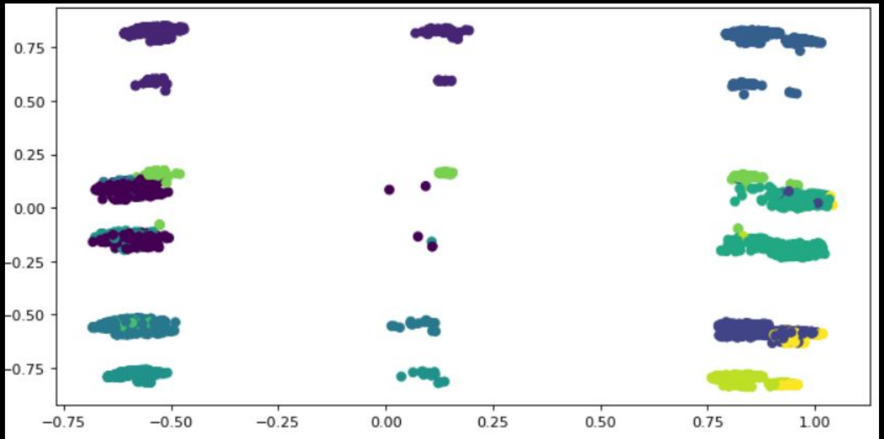

Figure 34: Plot of clusters

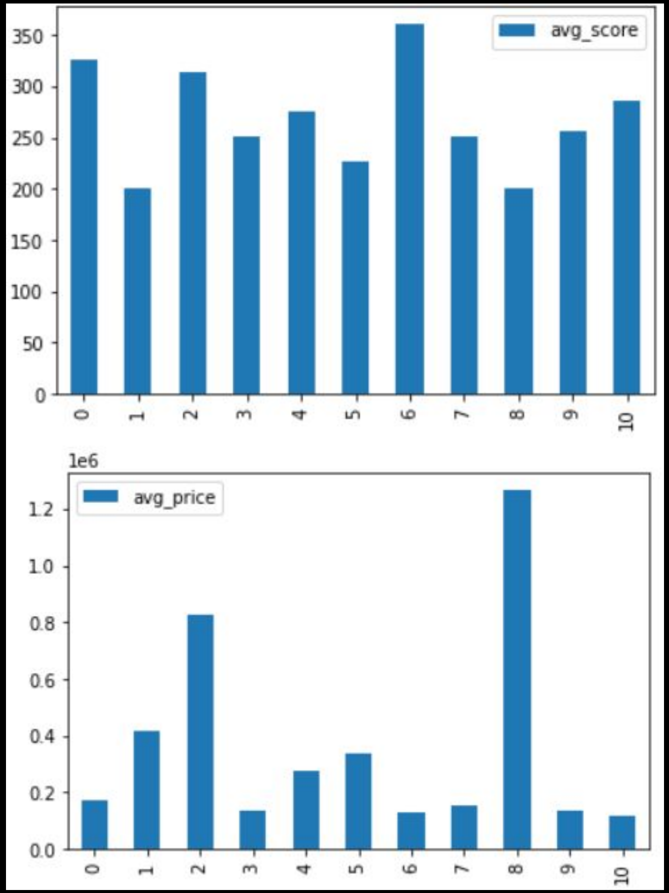

Figure 35: Average score & price per cluster

K-Means with NFT Score & PCA - Data Setup

trait_value token_id	3D Glasses	Alien	Ape	Bandana	Beanie	Big Beard	Big Shades	Black Lipstick	Blonde Bob
0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	187.340136
1	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000
2	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000
3	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000
4	0.0	0.0	0.0	0.0	0.0	0.0	51.474766	0.000000	0.000000

Figure 36: NFT Score for each token & trait

PCA

Attempt to reduce the number of factors

	0	1	2	3	4	5	6	7	8
0	2.868173	0.015396	0.077127	0.535661	-0.335486	-0.322381	0.452947	-0.589473	0.104624
1	-1.365979	0.277975	0.636110	0.359752	1.001173	0.704619	-0.480693	0.012484	-1.335782
2	1.197628	-0.102925	-0.634811	0.392736	1.543410	-0.065400	-0.379572	-0.437902	0.629324
3	-0.968424	0.216092	-2.133291	-0.859155	0.301874	-1.588515	-0.773756	-0.414124	1.316726
4	-1.473681	-0.152193	-1.082115	-1.106225	2.376299	-0.787320	0.089004	-1.688375	-0.995726

Figure 37: Principal Component Score

Pick the first 58 PC
(Cum Cont >= 70%)

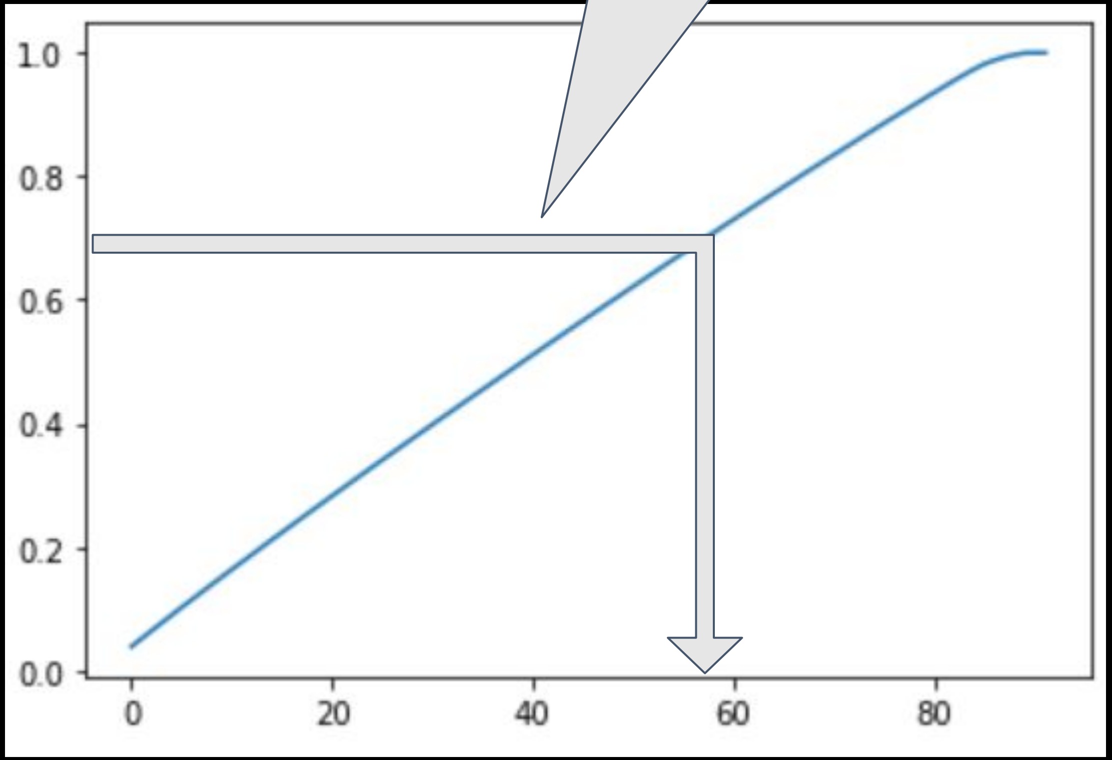

Figure 38: Cumulative Contribution

K-Means with NFT Score & PCA - Results

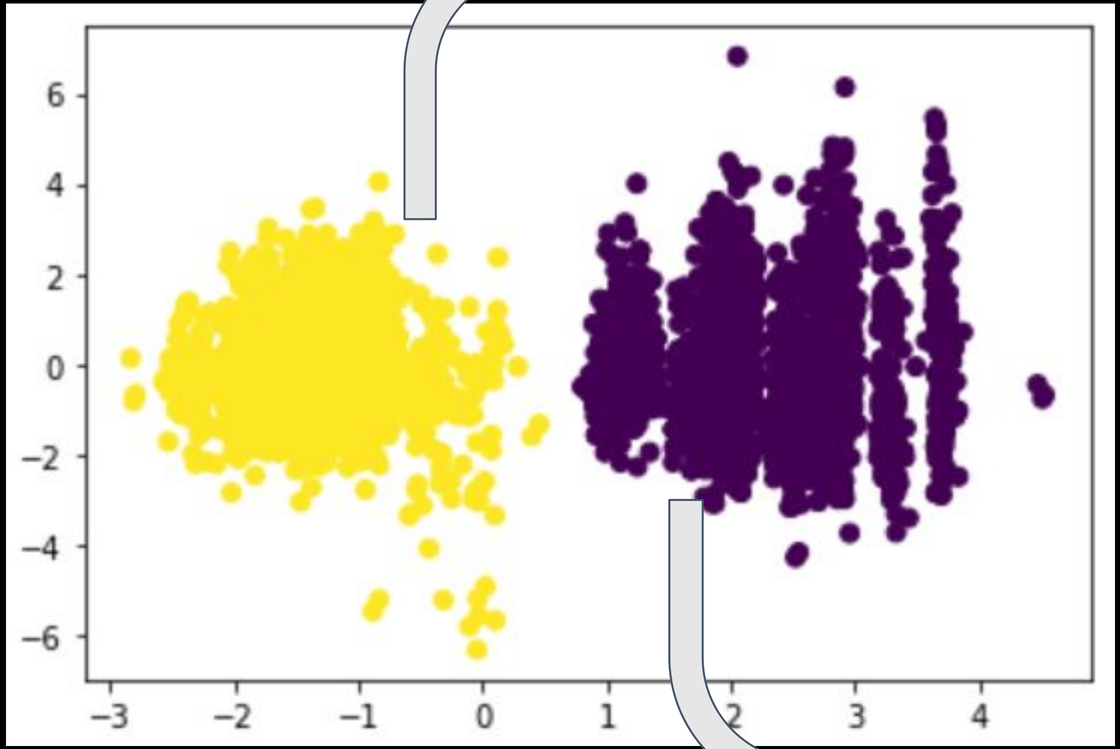

Figure 39: Plot of clusters

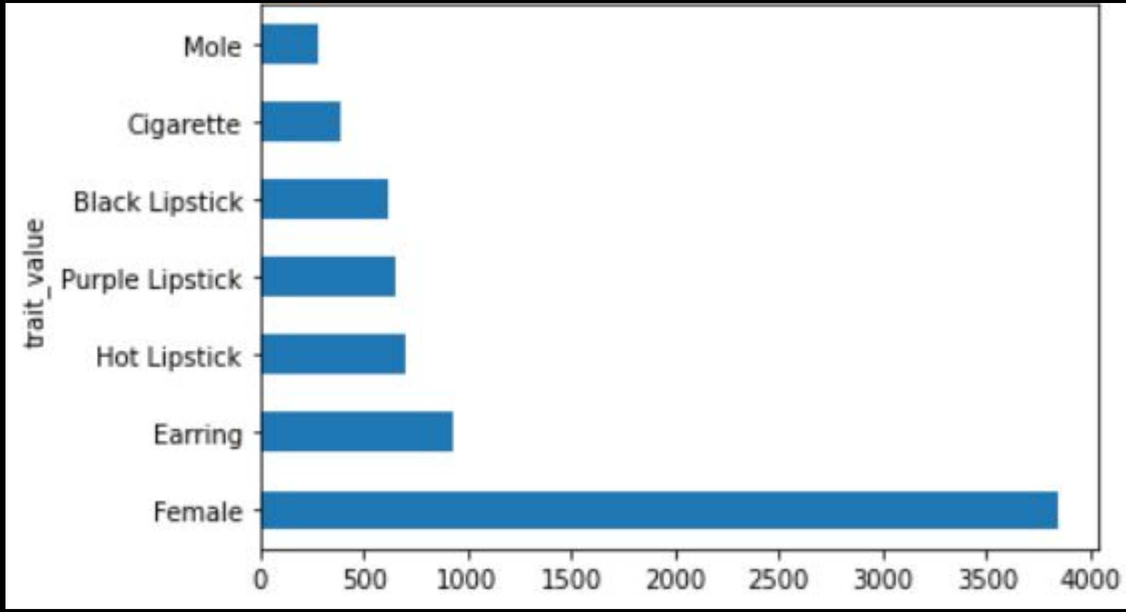

Figure 40: # of attributes for the cluster 1

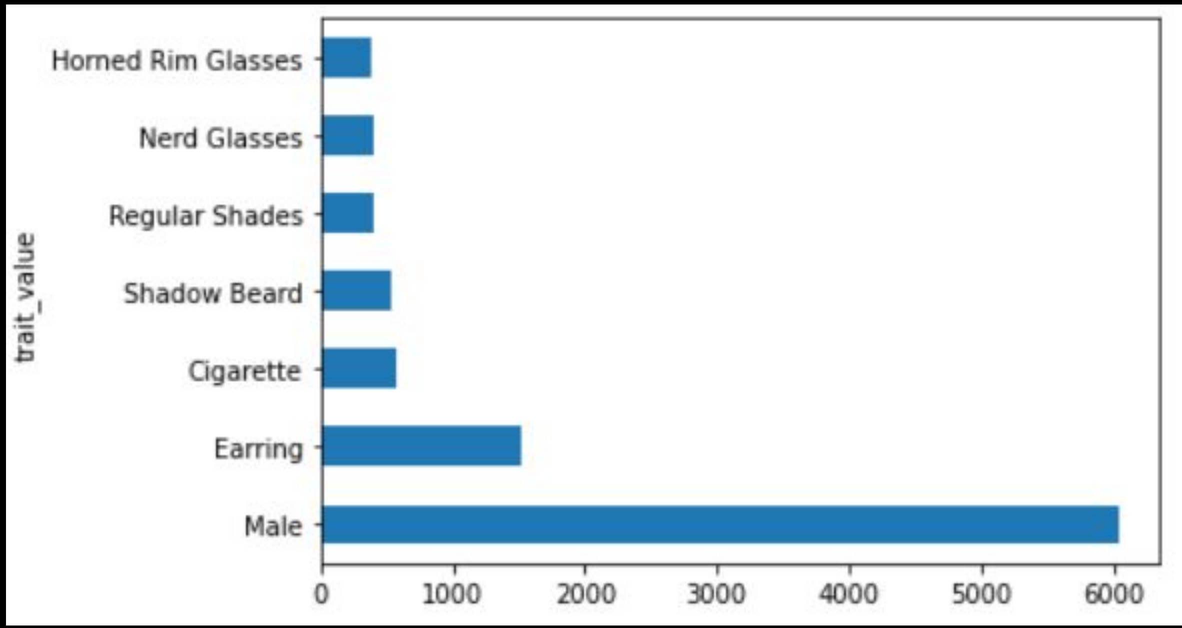

Figure 41: # of attributes for the cluster 2

Why Classification?

- Correlating parameters to exact price does not yield meaningful results
- Instead perform classification to detect the following states -
  - **profit** - token was sold for a higher price in a certain period
  - **nil** - token was not sold in a certain period
  - **loss** - token was sold for a lower price in a certain period
- We have tested the following classifiers taking a period as 1 year -
  - Logistic Regression
  - Gradient Boosted Classifier
- We test the classifiers using 2 scenarios -
  - Predict label as function of attributes
  - Predict label as function of attributes + last year’s movement

Data Setup, Features and Methodology

	type	num_attrs	attribute0	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	close2017	close2018	close2019	close2020	close2021
0	Female	3	Blonde Bob	Earring	Green Eye Shadow					0	0	0	0	0
1	Male	2	Mohawk	Smile						0	0	5144	36890	0
2	Female	1	Wild Hair							0	0	0	0	0
3	Male	3	Nerd Glasses	Pipe	Wild Hair					0	0	0	0	0
4	Male	4	Big Shades	Earring	Goat	Wild Hair				0	0	0	0	0

Figure 42: Data setup for Logistic Regression

- We create **attribute0-attribute6** and **type** as categorical variables
- This allows tokens with *similarly placed* attributes to be closer in space
- The **num_attrs** and **close2017-close2021** are numerical variables

Our study methodology is as follows -

- Pick a year (say 2020) and treat it as holdout data (i.e. unseen data)
- Cross validate the classifier on previous years data
- Fit the model on previous year's data and predict for holdout (2020)

Logistic Regression

- Scenario 1 cross-validation mean score: 0.390 +/- 0.014
- Scenario 2 cross-validation mean score: 0.621 +/- 0.024

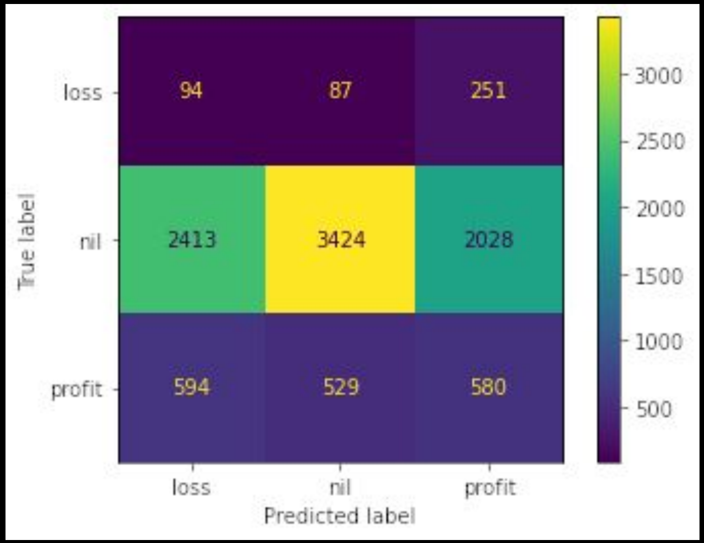

Figure 43: Confusion matrix for Logistic Regression Scenario 1

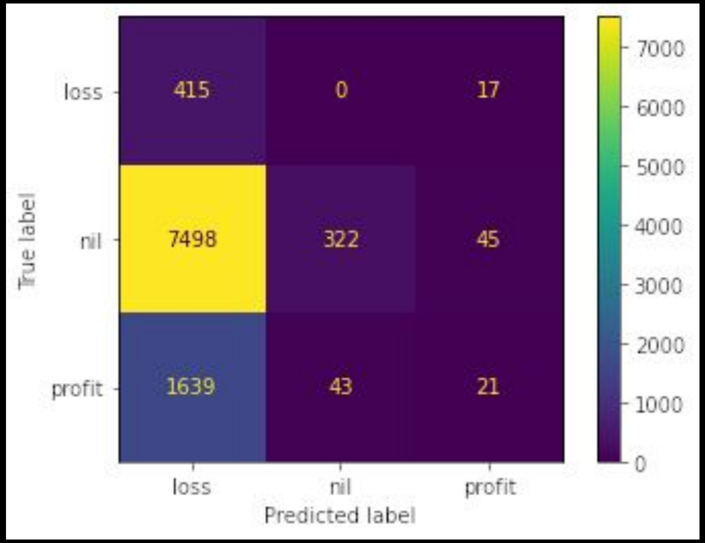

Figure 44: Confusion matrix for Logistic Regression + Thresholding

Scenario 1

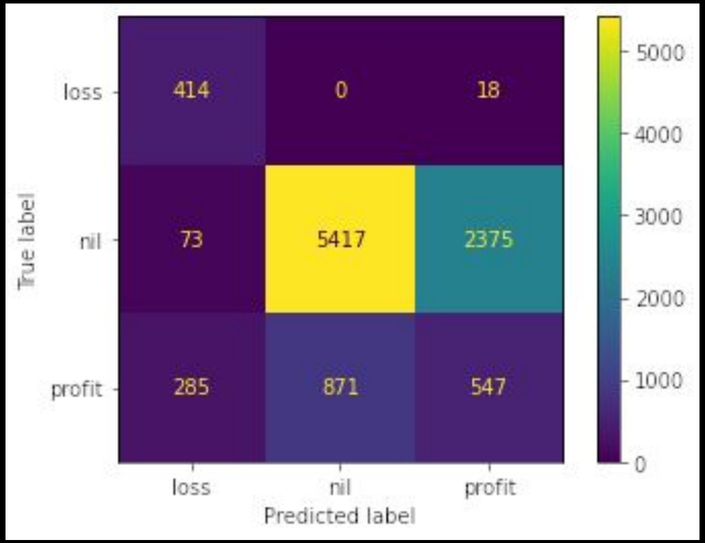

Figure 45: Confusion matrix for Logistic Regression Scenario 2

Gradient Boosted Classifier

- Scenario 1 cross-validation mean score: 0.782 +/- 0.002
- Scenario 2 cross-validation mean score: 0.810 +/- 0.007

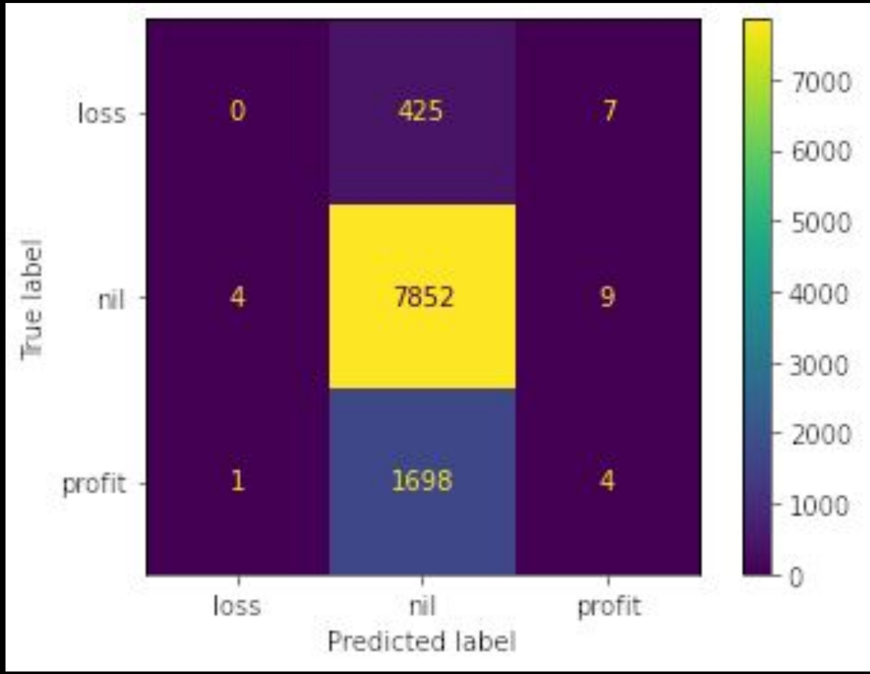

Figure 47: Confusion matrix for GBC Scenario 1

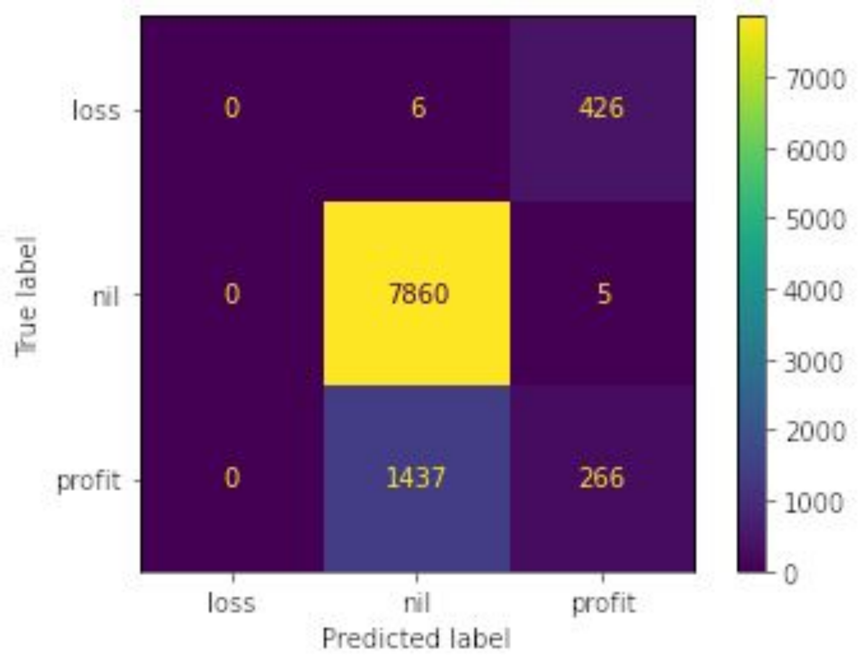

Figure 48: Confusion matrix for GBC Scenario 2

Analysis of predictions based on attributes

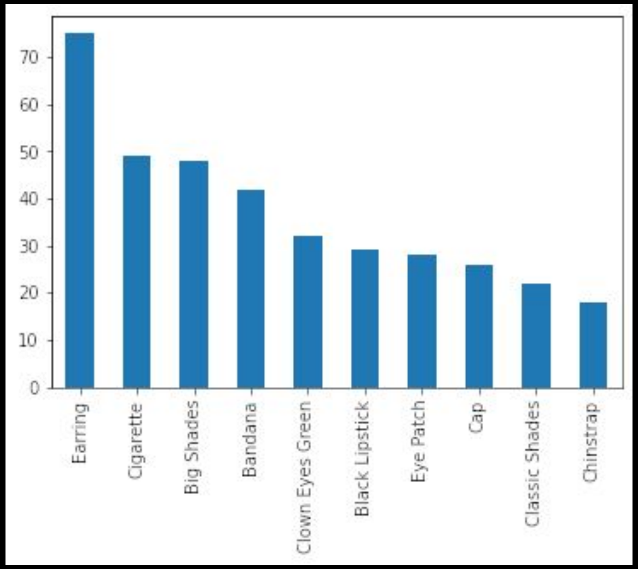

Figure 49: Top attribute0 count

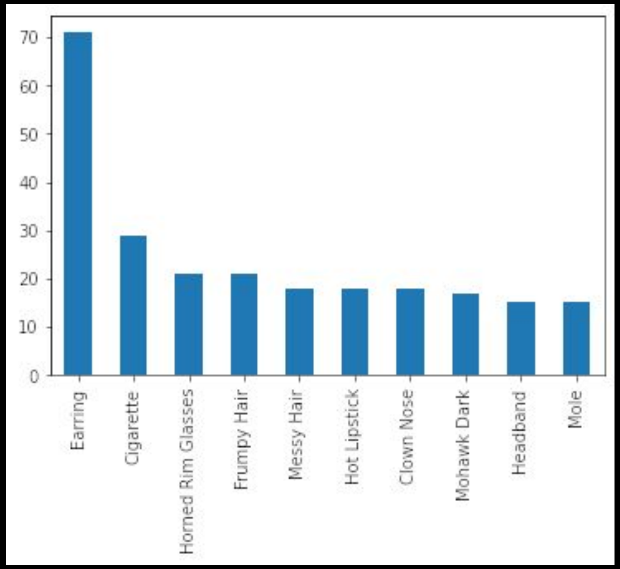

Figure 50: Top attribute1 count

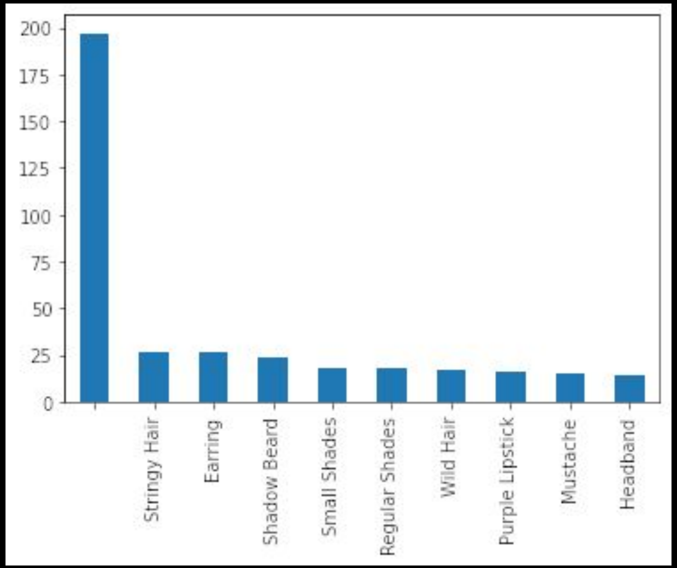

Figure 51: Top attribute2 count

Observations

- Classifier learns that “Earring”, “Cigarettes” are popular attributes
- Tokens with 2 attributes seem more likely to be profitable

Conclusion

Conclusion

Summary

- The price impact of attribute types and rarities have deteriorated over time.
- Current market conditions, sentiment, and social media may play bigger roles than in the past.

Limitations

- Data availability: less frequent transactions compared to other asset classes (e.g., price of financial instruments).

Future Model Enhancements

- Incorporate market condition data (e.g. number of daily sales, active wallets, total volume, etc.).
- Analyze crypto wallet activity directly on the blockchain.
- Incorporate sentiment analysis by extracting social media posts.
- Replicate methodology on other NFT collections (e.g. Meebits, BAYC).
- Backtest with trading strategies.

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print(‘thank you!’)