NFT Madness

Uncovering the key drivers of price in an NFT collection.

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What are the key drivers of price for a single NFT Collection?

What are NFTs?

NFT stands for Non-Fungible Token.

- Non-Fungible relates their unique nature
- Token expresses the collectible/*tradable* aspect of NFTs

So you can buy them, sell them… own them?

- This is where things start getting tricky
- NFT ownership is not like many other types of ownership
  - Once you buy an NFT you do own it, but what is “it” exactly?
  - The digital artwork is still reproducible and you do not necessarily own the rights to it
  - But while other people can make *copies* of it, you own the *original*
- Try to avoid the headache of reconciling this with “non-fungible”
  - meaning: can’t be replaced by something identical
  - At the end of the day this ownership is secured by the blockchain, with a validated smart contract witnessing to the event of you becoming the owner

The Collection

Mfers were created by twitter user Sartoshi who designed 10,000 one of a kind characters based of a meme in the crypto space. They were minted on 11-30-21 and are sold primarily on OpenSea.

Problem

Efficient Market Theory
- Highly Liquid
- Lots of Buyers and Sellers
- Perfect Information
- Market Competition
- History

NFT Markets
- Illiquid
- Few Buyers & Sellers
- Imperfect Information
- Unsaturated Markets & Unique Offerings
- Nascent

Why would anyone buy these things?

Alpha

There's money to be made.

Market Dynamics

Low liquidity, hedging, arbitrage.

Intrinsic Value

There must be something about them.

Arbitrage

Efficient Markets

Arbitrage is theoretically priced out by the perfect exchanges of buyers and sellers in equilibrium.

Imperfect Markets

Riskier, but arbitrage is theoretically more available.

02.

Data Science Process

Data Science Process

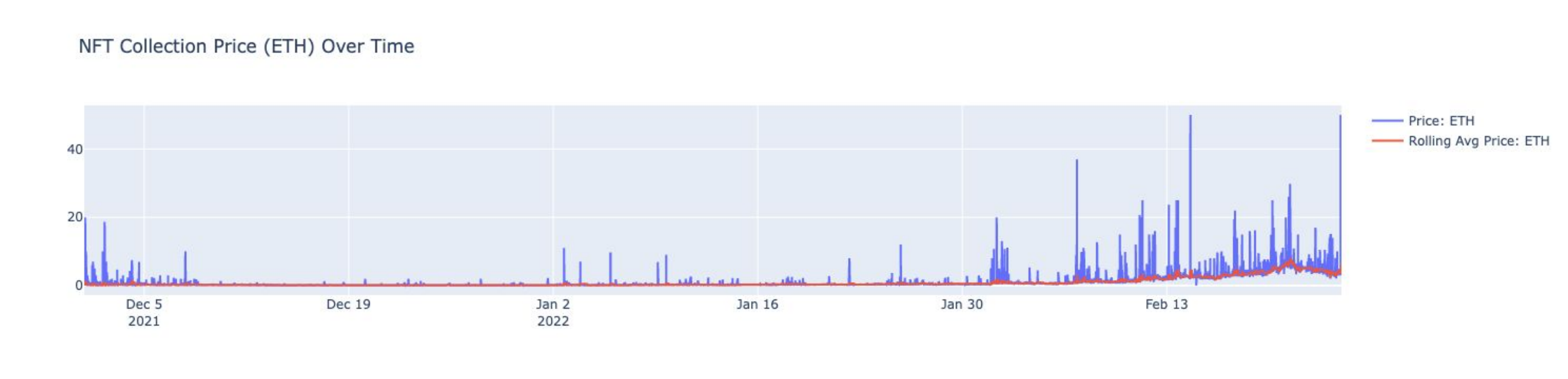
Data Collection

- Web APIs
  - Rarible
  - OpenSea
  - Moralis
- Collection and Asset level metadata
- Transactions and Feature-focused
- Nearly 20,000 txns
- 80+ features after engineering

4:20 WATCH Sub Lantern (gr... 6% have this trait	BACKGROUND Orange 20% have this trait	EYES Regular Eyes 72% have this trait
HEADPHONES Red Headphon... 7% have this trait	MOUTH Smile 79% have this trait	SHIRT Hoodie Down G... 6% have this trait
SHORT HAIR Messy Yellow 2% have this trait	SMOKE Cig Black 38% have this trait	TYPE Charcoal Mfer 40% have this trait

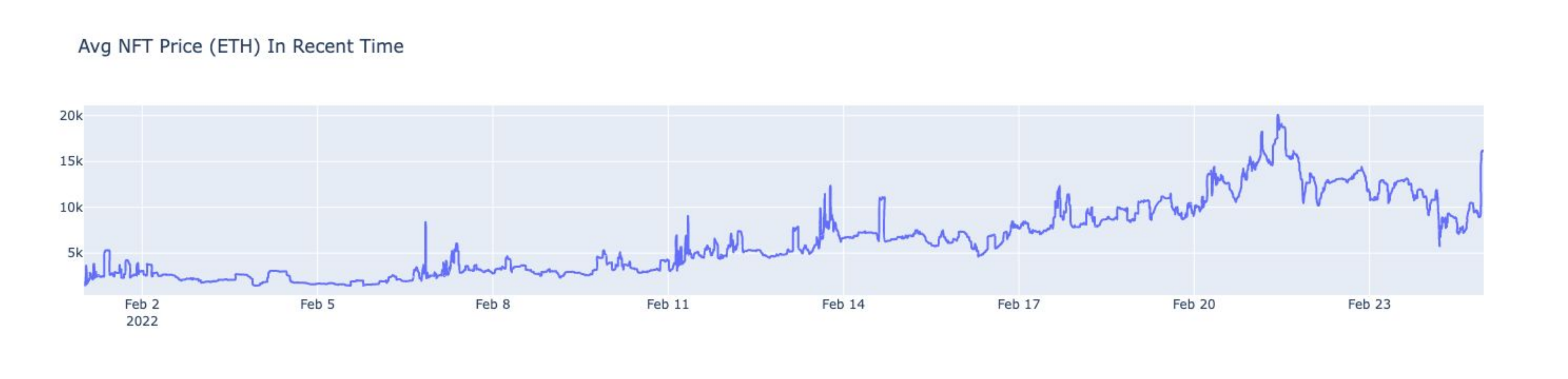
Exploratory Data Analysis

How has price changed over time for the assets in the collection?



Exploratory Data Analysis

Looking at just the rolling average price for the most recent 5000 transactions:



Exploratory Data Analysis

Fast Facts:

- Do to data collection limitations, I could not retrieve collection level metrics at any given date so these are this is current trading metadata.

- Because of this, these features were stagnant values and essentially learnable coefficients to models.

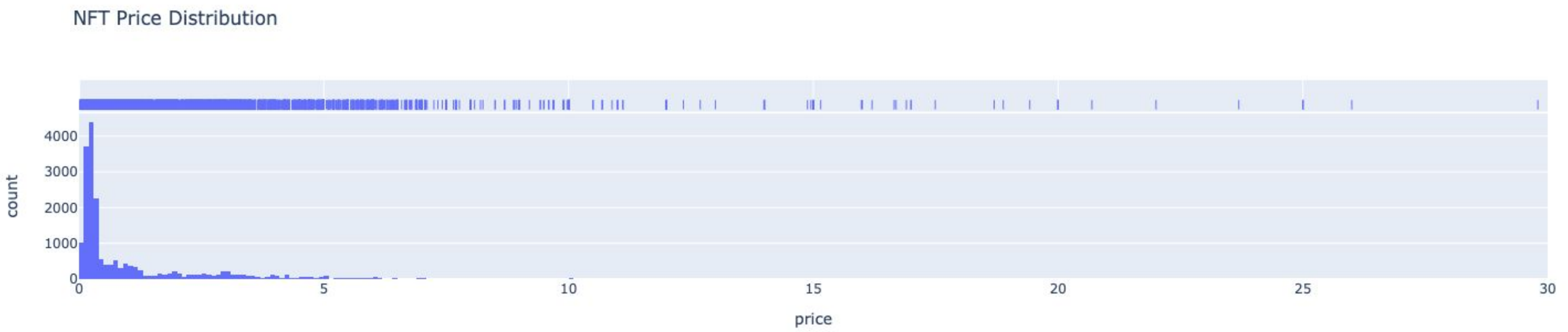
- Take note of:
  - Average price
  - Floor price
  - Discrepancies between average price at different horizons

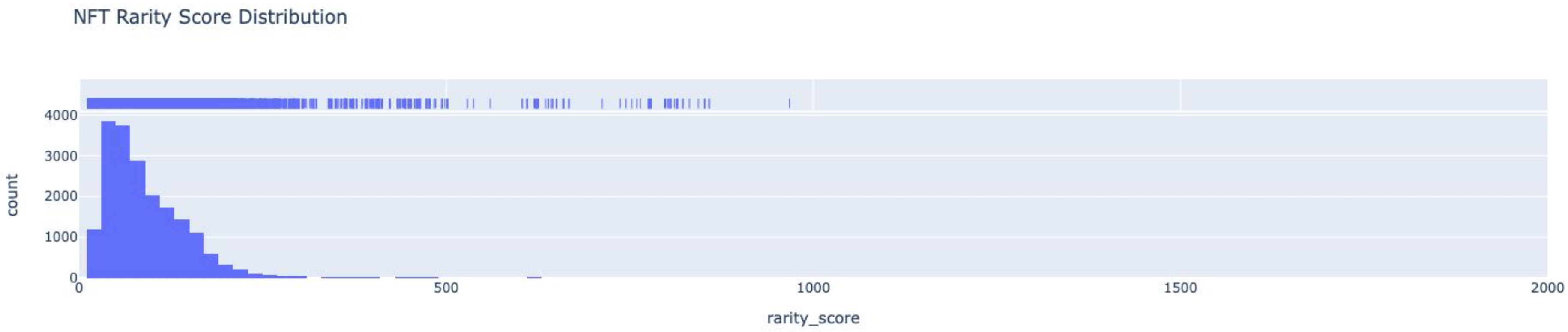
	stats
one_day_volume	262.080800
one_day_change	-0.012042
one_day_sales	81.000000
one_day_average_price	3.235565
seven_day_volume	4460.061519
seven_day_change	-0.436667
seven_day_sales	1082.000000
seven_day_average_price	4.122053
thirty_day_volume	19705.088064
thirty_day_change	15.286376
thirty_day_sales	7848.000000
thirty_day_average_price	2.510842
total_volume	23444.929392
total_sales	20434.000000
total_supply	10020.000000
count	10020.000000
num_owners	5072.000000
average_price	1.147349
num_reports	7.000000
market_cap	41302.972660
floor_price	2.790000

Exploratory Data Analysis

How does feature rarity affect price?

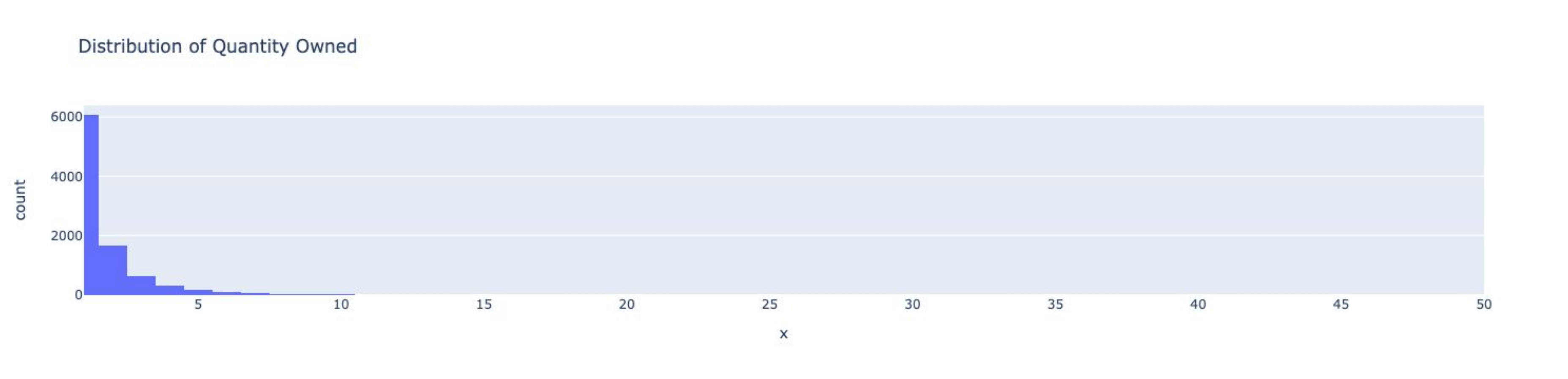
EDA: How are price and rarity distributed across the collection?





Exploratory Data Analysis

Who owns these NFTs?



- One address owns 1817 mfers!
- 9000 unique buyers, 7000 unique sellers

03.

Modeling

Modeling

The data:

- 20k transactions, 80 features
- 8977 unique tokens traded
- Features primarily span nft feature rarity, nft feature scores, and collection trading stats

The approach:

Preliminary Results

ML Methods

- Linear Regression +
- Every regressor scikit learn offers

Preliminary Results

- Uniform disaster
  - Drastic overfitting
  - Negative r2 Scores
  - Best r2: 0.21

Tweaks and Learning

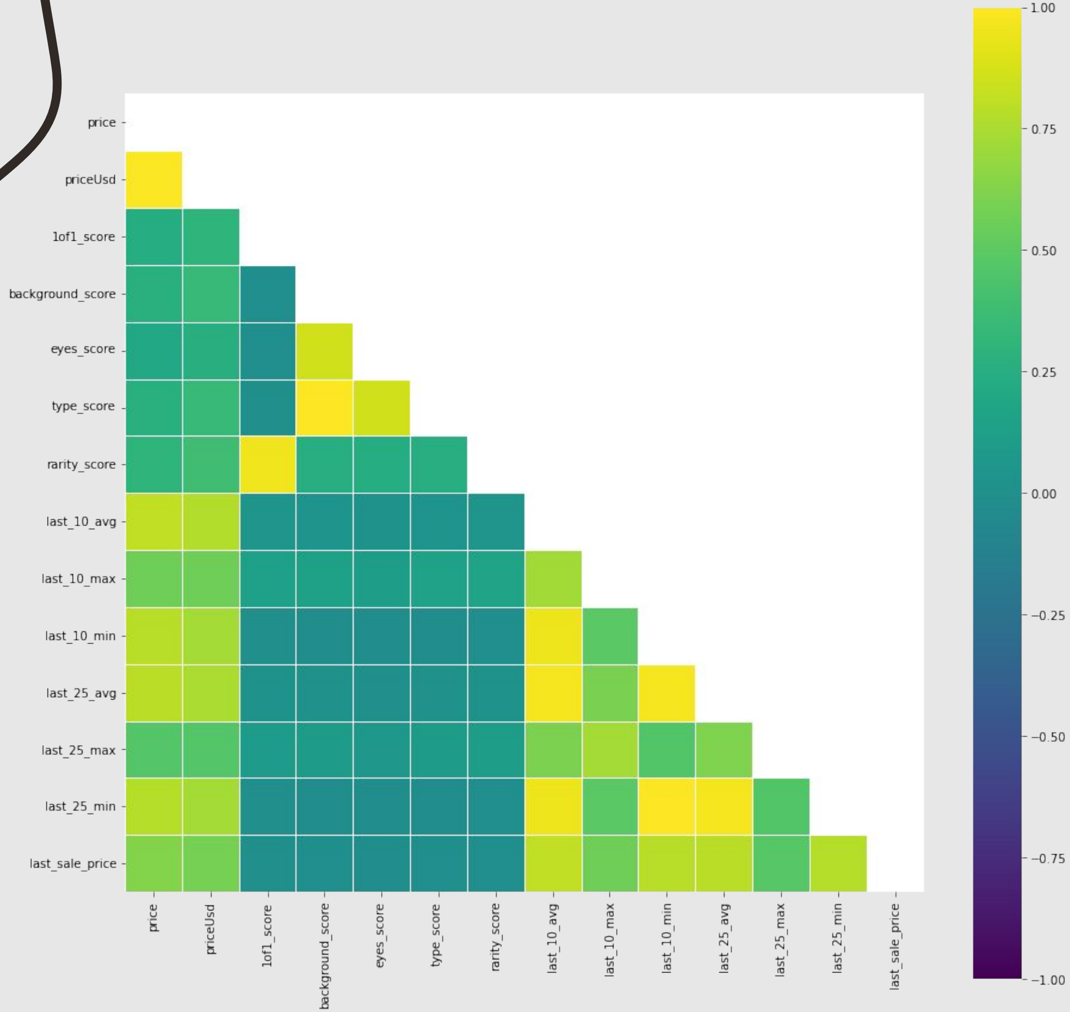
- Normalization and Regularization
    - little (<0.1) or negative effects on r2 scores
- Mix and matching features to include
    - Rarity scores influenced better performance than feature rarity
    - Total rarity score captured alone nearly all the effects of individual score columns
- Subsetting data
    - Modeling on recent transactions improved scores
    - Including the last transaction for each token improved scores

Breakthrough

- I was preoccupied with predicting value from an asset's singular features when in reality momentum was the single most important factor to price prediction.

- Though my dataset did not operate on a continuous time frame, it was still ordered and contiguous along a time frame.

- Borrowing from time series modeling techniques I extracted rolling averages looking back n prior transactions to engineer new features as well as the price of the last sale.



	price
last_10_avg	0.810
last_25_avg	0.795
last_10_min	0.784
last_25_min	0.780
last_sale_price	0.628
last_10_max	0.556
last_25_max	0.469
rarity_score	0.303
type_score	0.267
background_score	0.266
1of1_score	0.241
eyes_score	0.201
hat_over_headphones_score	0.088
hat_under_headphones_score	0.013
chain_score	0.010
short_hair_score	0.002
mouth_score	0.001
headphones_score	0.001
smoke_score	-0.004
watch_score	-0.012
shirt_score	-0.015
beard_score	-0.016
long_hair_score	-0.027

Final Model

1. **Linear Regression**
   Train R2: 0.8063
   Test R2: 0.8059
   RMSE: $2046
   MAE: $697

2. **Support Vector Machine**
   Train R2: 0.8625
   Test R2: 0.8632
   RMSE: $1789
   MAE: $901

	coefs
type_rarity	2088.204
type_score	857.607
hat_over_headphones_score	21.162
mouth_score	17.925
rarity_score	8.628
beard_score	2.897
chain_score	2.448
last_10_avg	0.554
last_25_avg	0.265
last_10_min	0.227

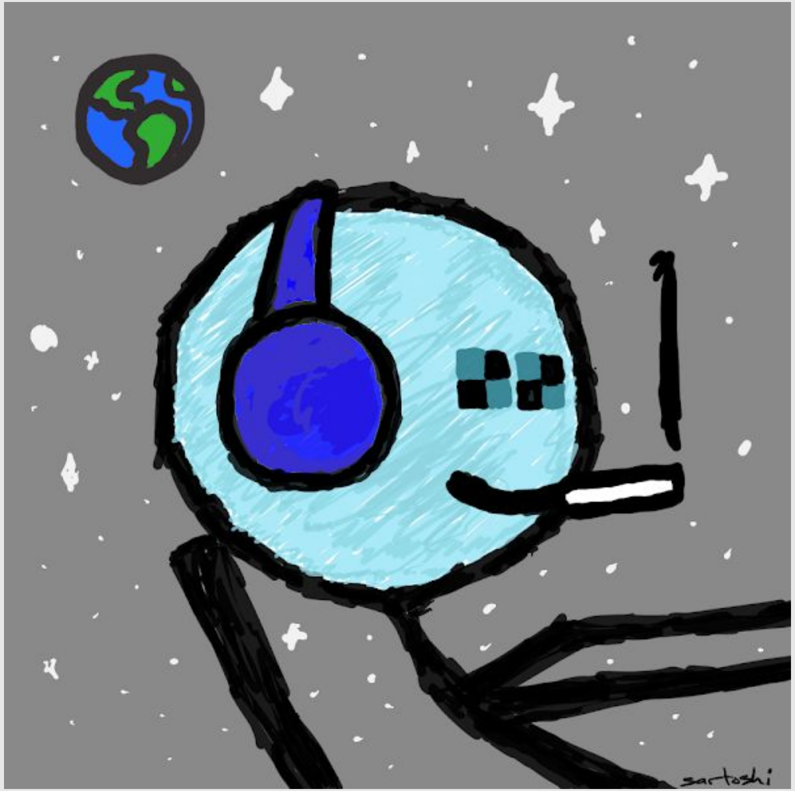
	coefs
smoke_score	-2.654
hat_under_headphones_score	-2.867
short_hair_score	-4.048
1of1_score	-4.807
watch_score	-5.660
shirt_score	-8.154
eyes_score	-18.714
long_hair_score	-19.361
last_sale_price	-139.360
background_score	-825.483

Final Model Comparison

A Note on Outliers

Mfers #904

- Space background, Alien eyes, Alien type
    - Rarity: 0.09%
    - Rarity Score: 852
- Generally feature-less
    - Only has 6 unique characteristics
    - Score lacks weighting methodology
- Timeline
    - Bought 10 ETH
    - Sold 50 ETH
    - Bid 80 ETH
    - Listed 100 ETH ($430k)



04.

Conclusions

What did I learn?

- Price movement in this NFT collection is heavily rooted in Momentum
- Momentum traders buy into trends; they sell losers trending down and buy winners trending up
- For those in touch with the language of the crypto space this actually isn't at all a foreign concept
  - "Aping" refers to collectively piling into a project whether it's a cheap alt-coin or nft collection
- Communities drive interest in projects in spaces like twitter and discord rousing others to ape in with them
- That's where I learned about this collection and they racquet around mfers is what made me cave and buy in
- The risk in momentum trading, especially with NFTs such as these that aren't designed with a long-term utility application in mind, is knowing when to get in and when to get out to get attractive returns and avoid being left with the bag
- In the models, being able to explain 80%+ of the variance in price primarily from incredibly near-sighted statistics confirms this explanation

#7510

- I bought in at 0.7 ETH at the beginning of February
- Sold a few weeks later for 1.7 ETH
- Two weeks after that #7510 sold for 3.5 ETH

Further Considerations

- Implementing a weighted scoring system for rarity score calculations
- Fitting a NN with similar results
- Classifying images of an NFT collection according to percentile rarity
- How easily can this all be transferred to any other collection?