Draft 1: Math 340 Final Paper

Abstract: Non-Fungible Tokens (NFTs) were invented in 2017 and in the past year there has been an exponential increase in their creation, trading, and most notably sale value. With maximum sales over 50 million dollars NFTs have become a notable financial interest for many collectors, traders, and artists as a new way to make and grow personal wealth. Through the blockchain, all the data on NFT transactions can be tacked and analyzed which was done by a blockchain analysis ground called Moonstream. With this data this study attempts to predict the future price of NFTs using those qualities of the NFTs creation and its trading. Using linear models, ridge regression model, robust regression, weighted least squares regression, and a random forest regressor the model made accurate predictions on a test set of NFT prices using the given explanatory variables. This data showed qualities that were not conducive to traditional linear modeling thus models excluding outliers, transforming variables, and testing interaction terms were also attempted confirming the observation of the impact of the mean transfer value on the final value of the NFTs.

Intro:

The introduction and excitement around Non-Fungible Tokens, NFTs, has raised both extreme excitement and extreme skepticism. The key innovation surrounding NFTs is the ability for an individual to own a piece of digital material. This is possible due to innovations in technology around blockchains and smart contracts. The recent activity in regard to NFTs has been performed on the Ethereum blockchain and all of the data for the study is collected from Ethereum based NFT activity. There is some worry that analyzing only a single blockchain could results in bias in the value as NFT has fees of around $40 per NFT creating biasing the value of the NFTs to be higher than other blockchains, such as Solana.

As NFTs have gained popularity there prices have also increased. In general NFT prices are denominated in ETH, the key cryptocurrency of Ethereum and the smallest unit of ETH is WEI. 10^18 WEI are equal to 1 Ethereum. This provides some concern for analysis of prices as Ethereum’s price fluctuates on top of the price changes of the actual underlying NFT. For this analysis I have chosen to look solely at the price of NFTs in ETH as predicting the underlying price fluctuations of ETH is an even harder to predict.

Predicting the price of NFTs is an interesting problem due to its financial importance to the NFTs and due to the breath of activity over the past year. Google trends shows that the popularity of NFTs are at their all time high since their creation in 2017. The current price of NFTs are qualitatively assumed to be a function of their exclusivity, visual characteristics, length of existence with older NFTs being viewed as being more valuable, and other characteristics such as network effects or utility. This study looks to analyze the impacts of the characteristics captured by the simple records of the NFTs, their trading patterns, and their minting patterns.

Background

In their recent paper, “Mapping the NFT revolution: market trends, trade networks, and visual features” Matthieu Nadini et.al. explore various features of the recent explosion in NFT trading and usage. They analyze the market trends of NFTs looking at the value of being in certain collections, the changes in the market over time, and which categories of products are the most prolificly traded. The authors split NFTs by type into art, collectible, games, metaverse, other, and utility. This classification helps understand the broader trends and movements in the cryptomarket. Through plotting the market transactions the paper shows the dominance of art transactions in the market while also reflecting the overall pattern of the recent spike in trading. In their investigation of the trader networks

Coding setup

Data Characteristics

Kaggle Analysis and Insignts