Predictors of NFT Prices:
An Automated Machine Learning Approach

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ABSTRACT

This article aims to broaden the understanding of the non-fungible tokens (NFTs) pricing determinants by investigating features, both market- and network-related aspects. NFTs are uniquely identifiable digital assets stored on the blockchain. Ownership is assigned through smart contracts and can be transferred or resold by the owner. The authors analyzed a comprehensive dataset from Signex.io with over 19,183 datapoints on NFT prices and NFT social communities using automated machine learning (AML), a suitable technique to investigate the most impactful factors due to a lack of knowledge on the exact determinants. Findings show that network factors are the most important pricing determinants: Twitter members followed by Discord members. Online communities drive the price of NFTs, but not in a linear fashion. Given the newness of the phenomenon and no agreed upon pricing models, this article contributes by using AML to discover the most relevant determinants of non-fungible tokens (NFT) prices.

KEYWORDS

AML, Artificial Intelligence, Digital Assets, NFTs, Non-fungible Tokens, Pricing, Social Metrics, Signex.io

INTRODUCTION

Non-fungible tokens (NFTs) are tradeable rights to digital assets whose ownership is recorded in smart contracts. In other words, they configure a new form of ownership that gives value to assets in a digital form. These digital assets - images, videos, characters, music, game record, text, virtual creations, among others - can be traded using digital cryptocurrency payments registered on the blockchain (e.g. Ethereum and Flow blockchains) (Bao & Roubaud, 2022; Dowling, 2022a, 2022b). The value of NFTs are hard to ascertain as they do not usually provide future cash flows, and are more akin to art than to stocks. Well known NFT projects that have skyrocketed in prices include *Crypto Punks* and *Bored Apes* whose prices have exceeded 100k USD per a single image in 2022.[1] Beeple's "Everydays: the First 5000 Days" sold for around $69 million, making it among the most expensive NFT ever minted.

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Unlike crypto coins and tokens that are fungible, NFTs are cryptographic assets that are non-fungibile. This means that each NFT item is a uniquely identified code with its own distinguishable metadata. Cryptocurrencies are interchangeable, and one digital coin is indistinguishable from another coin of the same ecosystem. The key characteristic of NFTs is the uniqueness of each token. Restricted ownership is granted by offering a unique digital certificate of ownership for the NFT, and their ownership records cannot be modified (Dowling, 2022b; Umar et al., 2022).

The trade volume of NFTs has increased in recent years, experiencing record sales especially after the Covid-19 pandemic. The effects of Covid-19 in the dynamics of financial markets, including cryptocurrencies movements, has started to be investigated (Conlon et al., 2020; Conlon & McGee, 2020; Goodell & Goutte, 2021a, 2021b). Mobility restrictions enhanced digital engagement and, consequently, the interest in cryptocurrencies and digital assets. In 2020, sales volume of NFTs was approximately 95 million US dollars. By the end of the second quarter of 2021, the NFTs trade reached 2.5 billion US dollars (Aharon & Demir, 2022).

The increase interest in NFTs started to be reflected in academia in the last few years. However, the topic is still under-researched in the fields of business, economics and finance despite its growing relevance. NFTs are considered one of the best recent economic innovations, creating new ways to tie technology and economic value and breaking down financial borders. NFTs democratized the access to digital assets and captured the interest of venture capitalists, Big Tech, digital and social media platforms (Laurence, 2021; Williams, 2022). Nevertheless, little is known about their pricing dynamic and relevant factors affecting it, especially network determinants impacts on prices.

Moreover, while previous studies aiming to investigate pricing determinants of NFTs made significant contributions (e.g., Horky et al., 2022; Kräussl & Tugnetti, 2022; Nadini et al., 2021), they mostly worked with partial datasets, metrics, and linear models. We aim to broaden the understanding of the NFTs pricing determinants by applying automated machine learning (AML). We used comprehensive data from *Signex.io*, a platform that helps investors to find NFT projects using general and social metrics from Twitter, Discord, Reddit and others.

We contribute to the field in two ways. First, we seek to provide further understanding on NFTs pricing determinants with special attention to network aspects. Big Tech and online communities and platforms act as connectors, influencing the evolution of the NFTs market. We develop a comprehensive model for NFTs pricing that includes network metrics, verifying that Big Tech are relevant and important predictors of NFT prices (Bao & Roubaud, 2022; Nobanee & Ellili, 2022).

Second, we contribute by using AML to identify the most relevant NFTs pricing determinants, considering the lack of a shared understanding of the exact predictors and their relationship with the target variables. AML has an advantage compared to linear models adopted in previous studies (e.g., Goldberg et al., 2021) as it explores complexity using big data and confirm empirical patterns using testing, validation, cross validation, and holdout samples. The best model is selected based on the data characteristics, considering simultaneously the predictive capacity of multiple models (Doornenbal et al., 2021). In our case, we tested 81 different models, and found the random forest model superior in its low prediction error. The study is relevant to NFT, crypto and Blockchain researchers who are interested in the business and economic aspects of the field. We also hope that practitioners, such as NFT project managers and investors in NFT projects, can be better informed about the pricing determinants.

The remainder of this article is organized as follows. Following this introduction, we present the literature review on NFTs and asset pricing. Next, we show the methodology and results. Finally, we discuss the findings and provide the conclusion of the study.

BACKGROUND

NFTs are assets in a digital form with blockchain-traded rights. These digital items are categorized in the NFT market according to their features, with the main categories being Art, Collectible, Games, Metaverse, and Utility (Aharon & Demir, 2022; Nadini et al., 2021). Kräussl and Tugnetti (2022) summarizes the main properties and examples of each NFT category. Art NFTs are assets with an artistic function. Collectible are multimedia collections of the same asset (video, images, etc.), for example the Bored Ape Yacht Club (BAYC). Gaming NFTs refer to the ownership of assets that can be used within a video game, such as CryptoKitties. Metaverse NFTs include expendable assets in a virtual universe, accessible through digital systems (computer, laptop, etc.), for instance the Decentraland. Finally, utility NFTs are assets that provide utility in the real or digital world, comprising finance, health, supply chain, or digital ID.

As it is a new phenomenon, to date only few studies approached NFTs in the fields of business, economics and finance despite its growing relevance. Our search for keywords "NFTs" OR "non-fungible token" in Scopus and Web of Science databases resulted in a total of 36 articles. The year of the first publication is 2016, with an increase of 71% in the number of publications by 2022. Figure 1 shows the evolution of publications number.

Most articles explore how these digital assets are being traded, interrelations between the prices of NFTs and other assets and cryptocurrencies, spillovers and connectedness of returns between NFTs and other financial assets, regulation and impacts on industries such as fashion and arts. Other research avenues that started to be explored are applications to the entrepreneurship, marketing, and consumer behaviour fields.

Figure 2 shows the co-occurrence network of articles on NFTs, illustrating the most relevant topics in the field so far. Keywords express the important terms and reveal the thematic field development (Bretas & Alon, 2021; Donthu et al., 2021). The two most discussed topics in the literature so far are (1) connectedness and spillovers and (2) intellectual property and contracts.

Network layout: Fruchterman & Reingold / Clustering algorithm: Walktrap / Normalization: association

There is an initial effort of scholars to understand the pricing dynamics of digital assets (Horky et al., 2022; Nadini et al., 2021). Table 1 summarizes the sample, variables, data sources, and methods

Figure 1. Number of publications

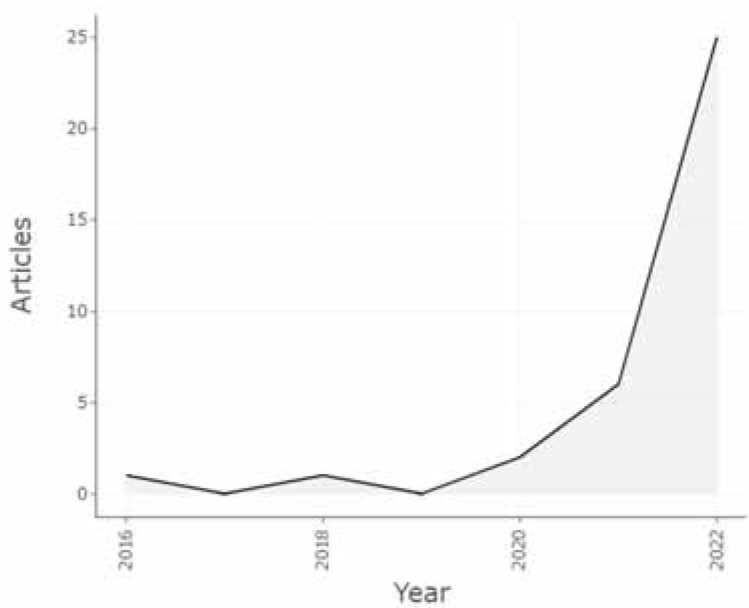
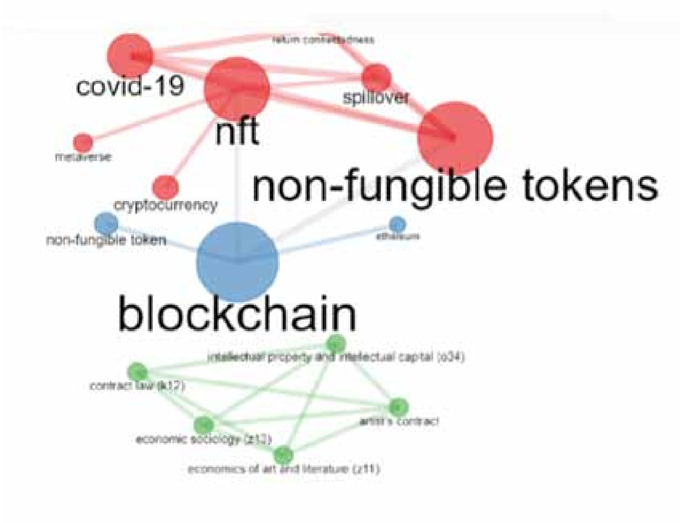


Figure 2. Co-occurrence network



used in these studies. The most common econometric models used to estimate NFT prices are hedonic regression models, repeat sales regressions, vector autoregressive models, and wavelet models (Kräussl & Tugnetti, 2022). The most common sources of data are nonfungible.com and coinmarketcap.com.

The main determinants of NFTs pricing identified in this scarce previous literature can be aggregated in three categories: market conditions, network factors and NFTs features (Figure 3). Among market conditions are the prices of cryptocurrencies, alternative asset classes (such as gold, crude oil, etc.), volatility, market sentiment (risk aversion, consumer confidence), market frictions and uncertainty, exchange rate of blockchain, NFT market size (sum of all selling prices, number of transactions), NFT market participants (buyers and sellers), and gas price. Network relates to the centrality of buyer and seller in the networks of NFT trades, network effects, network membership, and experts' opinions. Aspects related to NFTs features are sales history (price of NFTs previously sold within the same collection), visual features, size of the NFTs in bytes, and data format of the NFTs. Besides, predictability of future prices varies based on the NFT category (Nadini et al., 2021).

Previous results show effects of several determinants on NFTs pricing (Kräussl & Tugnetti, 2022): rarity, NFTs market size, NFT market participants, and favorable or unfavorable characteristics (Kong & Lin, 2021; Schaar & Kampakis, 2022); physical and virtual location in the metaverse (Goldberg et al., 2021); centrality on the trader network, sales history and visual characteristics (Nadini et al., 2021); selling rate and NFT features (ID and generation) (Kireyev & Lin, 2021); relationships between different projects, price of Bitcoin (BTC) and Ether (ETH) (Ante, 2021a, 2021b; Dowling, 2022b); bitcoins and alternative asset classes (bonds, crude oil, gold, stocks) (Umar et al., 2022). In some cases, results are somewhat contradictory. For instance, Ante (2021b) found that cryptocurrency considerably affect the pricing of NFTs, and Dowling's (2022b) spillover index shows low volatility transmissions and between NFT and cryptocurrency pricing, despite observing co-movement between the two sets of markets.

METHODOLOGY

Data

We identified the set of relevant determinants of NFT pricing in the literature, grouped in market conditions, network factors and NFTs features. These factors were applied in previous empirical

Table 1. Studies on asset pricing

Authors	Sample	Dependent variable	Measure	Independent variable	Measures	Data	Methods
Aharon and Demir (2021)	All trades in NFT market	NFTs market	Secondary market trades	Other asset classes	Equities, bonds, currencies, gold, oil, Ethereum	investing.com Nonfungible.com	TVP-VAR model
Ante (2021a)	1,231 daily observations	NFT variables	Dependencies between variables	NFT sales	Volume of NFT sales in USD	Nonfungible.com Bitfinex (bitfinex.com)	VAR model
				NFT wallets	Number of blockchain wallets involved with NFTs on a particular day		
				ETH price	Prices of Ether (ETH) in USD		
				BTC price	Prices of Bitcoin (BTC) in USD		
Ante (2021b)	14 NFT projects on the Ethereum blockchain	NFT projects	Dependencies between projects	NFT sales	Number of sales	Nonfungible.com	VAR model
				NFT volume	USD amount spent on sales		
				NFT wallets	Number of unique blockchain wallets involved in the trades		
Goldberg et al. (2021)	Decentraland 43,689 private parcels	Winning bids for parcels	Prices in USD	Shortest plaza distance	Dummy - access to a major plaza	Decentraland	OLS regression MGWR regression
				Shortest street distance	Dummy - access to multiple streets		
				Direct access to districts	Dummy - access to one of the 56 districts		
				SW-NE diagonal	Dummy - equal x and y coordinates		
Kong & Lin (2021)	CryptoPunk 20,841 transactions 6,598 unique tokens	NFTs market	CryptoPunk prices	Network effects	Growth of active wallets Growth of unique buyers Growth of unique sellers Growth of transactions for sales Growth of sales volume in USD Daily growth of ETH/USD exchange rates Daily growth of ETH trading volume	Larva Labs' website Nonfungible.com Yahoo! Finance Google Trends	Hedonic regression model
				Public attention	Search Volume Index (SVI) of the topic of "Ethereum"		
				Rarity	Type dummies (Alien, Ape, Zombie, and Female) 86 attribute dummies Number of attributes identified for each token		
				Primary sale	Dummy		
Maouchi et al. (2021)	9 DeFi tokens, 3 NFTs, Bitcoin, and Ethereum	Bubble	Dummy: bubble = 1	Trading volume	Traded volume expressed in ETH	coinmarketcap.com defipulse.com policyuncertainty.com St. Louis Fed's website Johns Hopkins University COVID-19 Data Repository	Logit, Probit, Tobit, and Linear regression
					Total Value Locked		
				COVID-19 pandemic	Global number of total cases		
				Economic uncertainty	Economic policy uncertainty		
				Volatility	CBOE Volatility Index		
				Investors' sentiment	Google Trend searches		
				Other asset classes	Gold and Brent prices		
Nadini et al. (2021)	6.1 million trades of 4.7 million NFTs in 160 cryptocurrencies	NFT's market	NFT's prices	Centrality on the trader network	Degree and PageRank centrality	Ethereum and WAX blockchains	Descriptive statistics Network of interactions Cluster analysis Machine learning
				Sales history	Prior probability of sale within the collection		
				Visual features	Principal components of visual features		
				Median price	Past median price of primary and secondary sales within the collection		

continued on the following page

Table 1. Continued

Authors	Sample	Dependent variable	Measure	Independent variable	Measures	Data	Methods
Dowling (2022a)	Decentraland 4936 trades of LAND	Pricing of parcels	Prices in USD	Market efficiency	Martingale market efficiency Improvement in efficiency over time	Decentraland	AVR, AP and DL consistent test
Dowling (2022b)	LAND tokens; CryptoPunk images; Axie Infinity game characters	NFTs market	Secondary market trades	Cryptocurrency market	Bitcoin and Ether	coinmarketcap.com	Generalized Impulse Responses matrix Wavelet coherence (SWC)
Ko et al. (2022)	92,371 trades of Sandbox, 68,500 trades of Decentraland, and 10,704 trades of Cryptopunks	NFTs market	Average price	Other asset classes	Stock, bonds, US dollar, commodity index, and cryptocurrencies (Bitcoin and Ethereum)	Yahoo! Finance WRDS database coinmarketcap.com S&P 500 index MSCI World index MSCI Emerging Market index Pimco index Invesco DB Commodity index SPDR Gold Shares	Pearson correlations, Gerber Statistic, Volatility spillover index, TVP-VAR
Schaar & Kampakis (2022)	CryptoPunk 11,864 transactions	NFTs market	CryptoPunk prices	Rarity	Type dummies (Alien, Ape, Zombie, and Female) 86 attribute dummies Number of attributes identified for each token	Larva Labs' website	Hedonic regression model
Umar et al. (2022)	Transactions in three subintervals (pandemic, first and second year of the pandemic)	NFTs market	NFTs daily average transaction price	Other asset classes	Bitcoin, bonds, equity, gold and oil	Bloomberg terminals Nonfungible.com	Wavelet coherence (SWC)
Vidal-Tomás (2022)	129 play-to-earn tokens and 84 metaverse tokens	Short- and long-run performance	Average first-day returns Average buy-and-hold returns	Play-to-earn/ metaverse tokens	Closing and opening prices	CoinGecko database	Pearson and Kendall correlations, BSADF, Wavelet coherence
		NFTs market	Token prices	Cryptocurrency market	CCi30 index		
Yousaf and Yarovaya (2022)	Five NFTs and five Defi assets	NFTs and Defi assets	Average returns	Other asset classes	Oil, gold, Bitcoin, and S&P 500	coinmarketcap.com Bloomberg	TVP-VAR model BEKK-GARCH model

studies and AML helps to further improve knowledge on the relationships between them and NFT pricing. We included in the empirical study variables that capture the different dimensions of the NFT pricing determinants identified in the literature (market conditions, network factors, and NFTs features). Table 2 shows the variables selected, the dimension of the NFT pricing determinants they capture, their description and the method of extraction.

We used data from *Signex.io*, a platform that tracks NFTs and their characteristics, from the period January 2022 to July 2022. It helps investors to find NFT projects using general and social metrics from Twitter (microblogging and social networking service), Discord (VoIP – voice over Internet Protocol and instant messaging social platform), Reddit (social news aggregation, content rating, and discussion website) and others. It also tracks whale activities. Users can track on the platform the most important data points of an NFT, such as total supply, the number of unique owners, trading volume, and social media growth.

Figure 3. NFTs pricing determinants

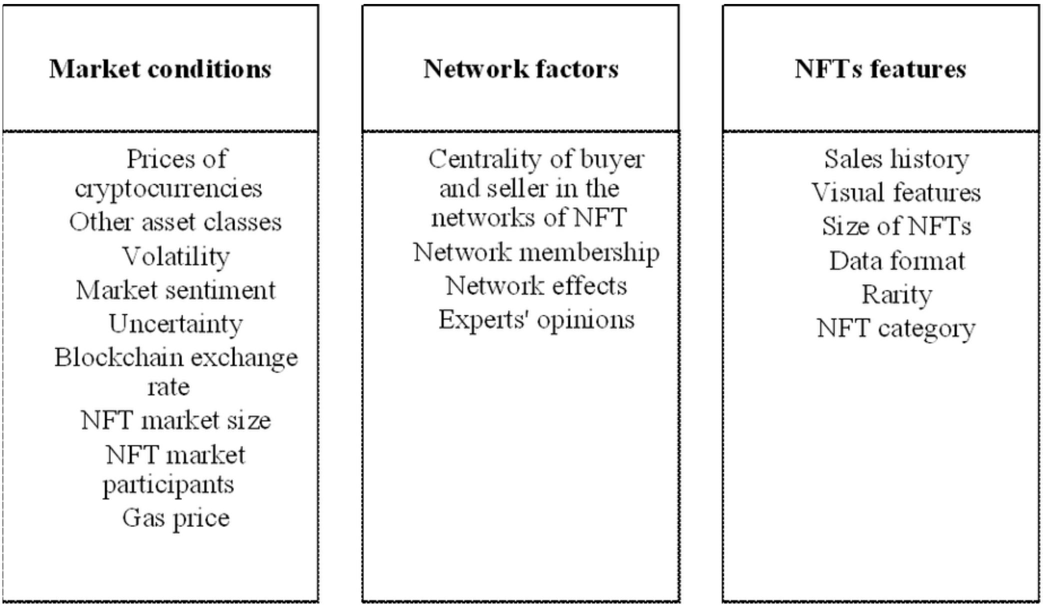


Table 2. Variables

Variable	Dimension	Description	Method of Extraction
Dependent variable			
avgPrice		Average daily price	OpenSea API
Independent variables			
ethPrice	Market conditions	ETH USD price value	OpenSea API
ethVolume	Market conditions	ETH USD volume value	OpenSea API
name	NFT features	Categorical	OpenSea API
discord members	Network factors	Number of members	Discord API
discordActivityTodayValue	Network factors	Discord activity - today value	Discord API
discordActivityYesterdayValue	Network factors	Discord activity - yesterday value	Discord API - Historical
Twitter followers	Network factors	Number of followers	Twitter API
Score	Network factors	Score based on social metrics	Calculated via Signex formula*
Sentiments		4 Factor sentiment analysis	Open source NLTK + customised Signex logic
Date	Network factors	Day of week	

Signex combines data from the “On-Chain” and “Off-Chain” to establish a model that explains the effect of social data on the “On-Chain” activity. “On-chain” uses available chain-based API integrations and scanning of the blockchain. Signex tracks wallet activities, marks and identifies whales, tracks crypto currencies, gas fees and more. Additionally gathering On-Chain historical data back in time allows better pattern recognition and deeper insights. “Off-chain” gathers data points from multiple social sources such as Twitter, Discord, Reddit and etc, Signex has developed a multi-channel data aggregation system via API integrations, real time events, scraping of news and social hubs, analyzing sentiments and unique scoring system based on social activities.

Signex is a more suitable data source compared to others adopted in previous studies as it collects not only On-Chain data aka Blockchain, but social information related to the NFT projects as well. As most of the data sources available today focus on only one segment of the data collection, they create models that encapsulate only features related to the specific data they collect. Signex on the other hand collects both data sources and focuses on combining the data points to create a singular unique model to represent both factors(social/blockchain) for each NFT project.

Automated Machine Learning

We use Automated Machine Learning (AML) technology to select best fitting model for explanation of NFTs pricing determinants. AML is superior to traditional linear regressions by examining many types of models simultaneously, non-linearities, and making no assumptions about predictor distribution and stochastic properties. By testing multiple models on data not seen, the resulting model tend to be more robust, and properly fitted (Krakovska et al., 2019; Lindner et al., 2022; Seeber et al., 2022). AML minimizes predictive errors, explores patterns in the data and makes predictions based on these patterns through algorithmic learning, finding optimal solutions between a set of variables and a target – in this study, the NFTs pricing (Doornenbal et al., 2021; von Krogh, 2018). Lindner et al. (2022) also suggested that machine learning is robust with respect to collinearity when large number of variables are investigated.

AML is suitable to research settings in which there is lack of shared understanding about the predictors and relationships between them and target variables, that is the case of NFTs pricing determinants (Seeber et al., 2022). A target (dependent) variable is selected, and suitable models are suggested through machine learning using algorithms for accurate predictions (Larsen & Becker, 2021). This process is divided into three phases: data partitioning, training and hyperparameter tuning, and model scoring (Alon et al., 2022). In our case, we analyzed 81 different machine learning models and found that Random Forest provided the best results. The model achieved an R square of 47% and 44% for cross validation and holdout samples.

We use the program DataRobot and apply a time-aware model to control for autocorrelation. We implemented it by using out-of-time validation (OTV) date/time partitioning, that is used when data is time-relevant and the goal is to predict the target value on each individual row.

Figure 4 shows the blueprint used for modelling. By coupling an automated machine learning model with a preprocessing step, the blueprint maps inputs to predictions.

The best model recommended for deployment is the Random Forest (MSE) Regressor. Figure 5 shows the model performance. Random forests are an ensemble method where hundreds (or thousands) of individual decision trees are fit to bootstrap re-samples of the original dataset, with each tree being allowed to use a random selection of N variables, where N is the major configurable parameter of this algorithm (Breiman, 1999).

Ensembling many re-sampled decision trees serves to reduce their variance, producing more stable estimators that generalize well out-of-sample. Random forests are extrememly hard to over-fit, very accurate, generalize well, and require little tuning, all of which are desirable properties in a predictive algorithm. Random forests have recently been overshadowed by Gradient Boosting Machines (which DataRobot also implements) but enjoy a major advantage in that they are embarrassingly parallel and therefore scale much better to larger datasets (Ho, 1995; Liaw & Wiener, 2001).

A further refinement of this method is the “ExtraTrees” model, which is a random forest with more randomness: the splits considered for each variable are also random. This decreases the variance of the model but potentially increases its bias. The ExtraTrees models has an additional advantage

Figure 4. Model blueprint

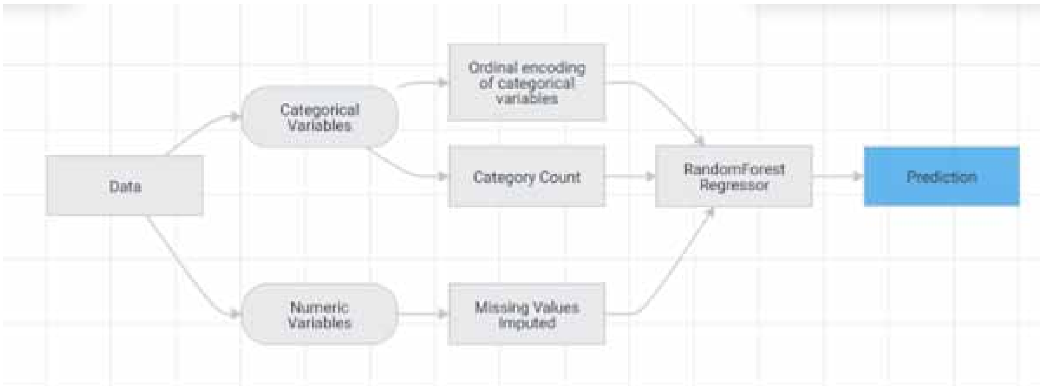
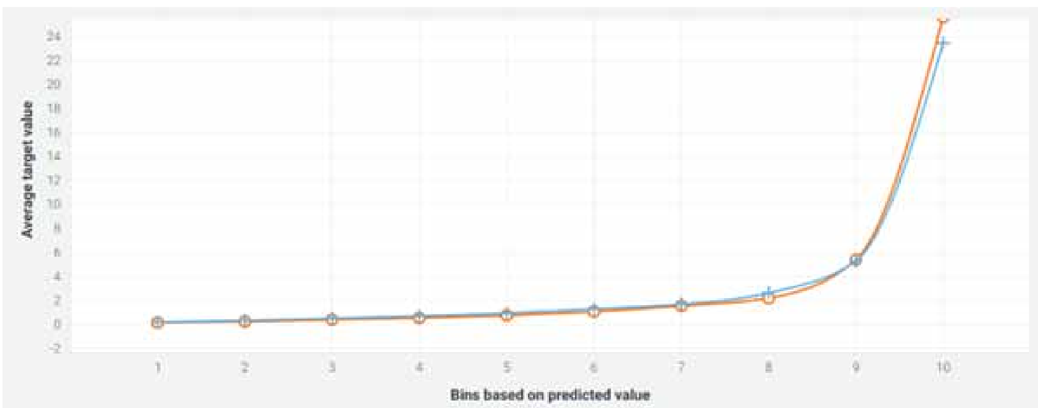


Figure 5. Model performance



in that it is computationally very efficient: no sorting of the input data is required to find the splits, because they are random (Geurts et al., 2006).

RESULTS

The variables considered in this study capture the different dimensions of the NFT pricing determinants (market conditions, network factors, and NFTs features). Table 3 shows the descriptive statistics for the variables adopted in the study.

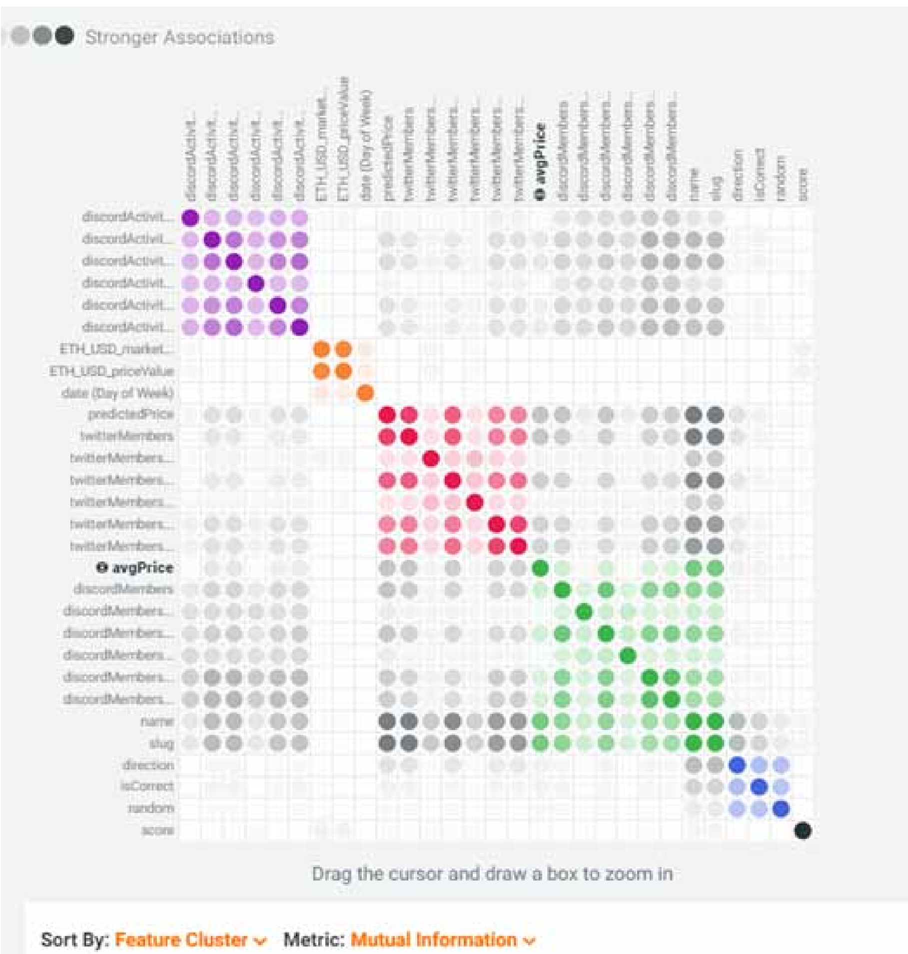
The feature associations matrix shows the associations within the data (Figure 6). The matrix reveals the detected relationships between categorical and continuous data, the extent variables depend on each other, and the clusters, denoted by colour, in which variables are partitioned based on their similarity. It is possible to observe in the matrix the nature and strength of the associations and detect pairwise association clusters.

AML normalizes the data and uses adequate models to fit the data distribution. Thus, normalization tests are not required (Alon et al., 2022). Feature impact (Figure 7) reveals which features are important to the model outcome and are driving model decisions the most. It also allows the identification of unimportant or redundant features that can be dropped to improve model performance. We can observe

Table 3. Descriptive statistics

Feature name	Index	Var type	Unique	Missing	Mean	Std Dev	Median	Min	Max
avgPrice	10	numerical	15,542	0	3.62	9.71	0.86	0.01	81.19
[Target Leakage] name	1	categorical	121	0					
twitterMembers	4	numerical	10,639	2,701	127,554	344,925	41,946	0	3,406,952
discordMembers	3	numerical	7,033	4,684	54,341	92,044	25,688	131	800,000
discordActivityTodayValue	5	numerical	3,593	7,152	2,234	4,631	587	1	65,099
discordActivity_ yesterdayValue	6	numerical	3,980	7,635	2,883	5,787	967	1	75,585
score	7	numerical	15,399	0	24.65	20.55	20.19	0	100
date (Day of Week)	2	categorical	7	0					
ETH_USD_to...olumeValue	9	numerical	155	0	3.14E+11	7.03E+10	3.33E+11	1.29E+11	4.23E+11
ETH_USD_priceValue	8	numerical	155	0	2,616	591	2,772	1,069	3,522

Figure 6. Feature association matrix



that Ether prices and volume have the smallest effect on the outcomes of the model, meaning they are not strong predictors of NFT prices.

Figure 8 shows the resultant feature effects, meaning the effect of changes in the value of each feature on the model's predictions. It displays how a model understands the relationship between each feature and the target, with the features sorted by the feature impact. The most important feature is assigned 100%. We identified Twitter members as the most important feature, followed by Discord members. These findings reveal the relevance of online communities in promoting NFTs and affecting pricing.

The Partial Dependence (Average Partial Dependence) of the most important features revealed (Twitter members, Discord members, Discord activity yesterday, Score, Discord activity today, Ether (ETH) price, and ETH volume) is shown in Figures 9 to 15. The charts illustrate the marginal effect lineof the feature on the target variable (NFTs pricing) and indicates if their relationship is linear, monotonic, or complex. A change in the feature's value, being all other factors the same, impacts the predictions of the model. We can identify non-linearities between the target and features, as observed in real-world scenarios.

CONCLUSION

The article makes a contribution to our understanding of NFT prices, showing in particular the relative importance of social networks such as Twitter and Discord. NFT characterizes a new breed of assets on the Web3. Web3 is the new iteration of the internet that incorporates decentralization, blockchain technologies, and token-based economics. Unlike Web2 where Big Tech has dominated, Web3 is

Figure 7. Feature impact

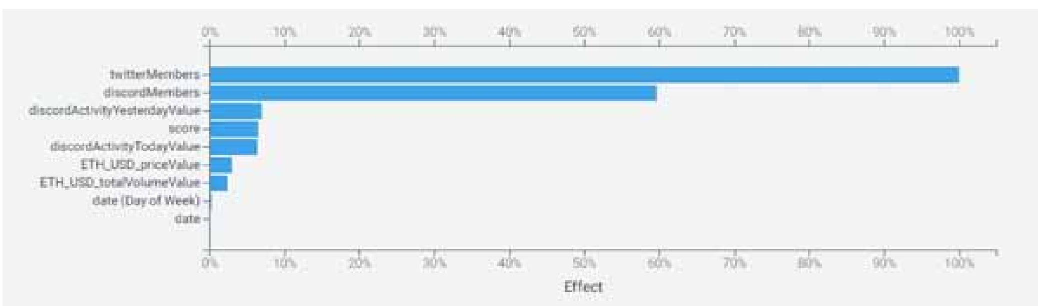


Figure 8. Feature effects

Figure 9. AML results – Twitter members

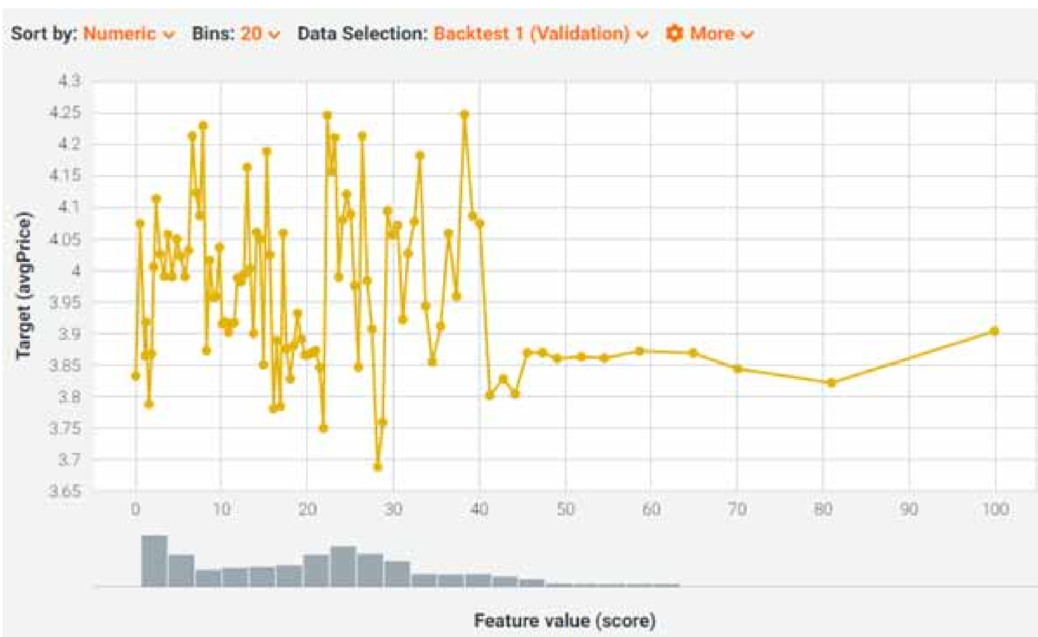
Figure 10. AML results – Discord members

based on communities, peer to peer communications, and verification process that is autonomous and decentralized. To date, most NFT projects are still based on Ethereum, although Polygon is gaining ground fast. The Ethereum blockchain transitioned from proof of work to proof of stake, and other upgrades to increase functionality.

Our research suggests that Twitter and Discord are relevant and important predictors of NFT prices, showing the ongoing relevance of Big Tech in promoting NFTs. Discord on the other hand is a bit different than Twitter in that it is community based (rather than individual base) and offers multiple channels (text, video and voice) for peer to peer engagement. While bigger communities tend to command higher prices for their NFTs, this relationship goes through peaks and troughs. Discord membership shows early peak around 50k members, Twitter is around 24k. Above that, there

Figure 11. AML results – Discord activity yesterday

Figure 12. AML results – Score



are significant troughs. This may suggest that bigger is not always better and that tighter and perhaps more focused communities can provide a better price outcome. One can also see from the results that Discord activities are significant predictors too. Here too one can see a drop beyond a certain level, perhaps indicating *bots* may be involved and have a negative impact on price performance. *Bots* are autonomous programs, create a lot of noise and appearance of activity on the internet, and are

Figure 13. AML results – Discord activity today

Figure 14. AML results – ETH price

designed to promote products, people and ideas. The use of bots to create value has been contested by Elon Musk in relation to his 2022 potential purchase of Twitter.

In addition, our analysis shows that Ether prices and volume are not strong predictors of NFT prices as we expected. As prices of most NFTs are in Ether, we expected a negative relationship between price and demand. Lower Ether prices means that most NFTs are trading in lower dollar prices. This hypothesis might even be reversed because it seems that when Ether prices are above 3300, NFT prices rose along. We may surmise from this that the overall market conditions of Ether positively affect NFT prices even though prices are denominated in Ethe. In that way. we provide a contribution not only to NFT, crypto and Blockchain researchers who are interested in the business

Figure 15. AML results – ETH volume

and economic aspects of NFTs, but also to practitioners, such as NFT project managers and investors in NFT projects, who can be better informed about the relevant pricing determinants.

As NFT research is in its infancy, it is not hard to see all sort of ways that this research can be extended. For example, what causes the curvilinear effect in communities? What are the determinants of community size and growth? What is the effect of sentiments on NFT prices? What can we learn about community management from NFT projects? NFT prices, and perhaps for all the crypto space, have gone through a major correction in 2022. Will the determinants of NFT prices change over time as the asset class matures.

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ENDNOTE

1 Note the value of NFTs is often in Ether rather than dollars https://www.coindesk.com/business/2022/08/22/cryptopunks-briefly-flip-bored-apes-as-nft-prices-continue-to-crater/

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