

Metasurance

Blockchain-based Insurance Administration System
with ML-driven Dynamic Pricing for New Metaverse
Products

By Priyanka Sachan (1901CS43)



01

NFT RISK | INSURANCE

NFTs can get lost,
stolen or destroyed.

02

PROBLEM STATEMENT

What to do?

03

PI: NFT VALUATION

NFT Price Appraisal
in Turbulent Market



04

PERFORMANCE ANALYSIS

Price Prediction with
different feature set

05

IMPROVEMNETS & CONCLUSION

What Next?



Pretext | NFTs

NFTs

[*ˈen,ˈef,ˈtēs*]

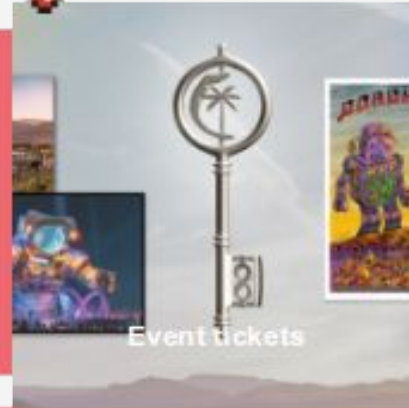
noun COMPUTING

Cryptographic tokens that live on blockchain

– each with its own unique identification codes and metadata that can not be replicated.



Examples of NFT use-cases



Membership access



Financial collaterals



Authentication tool

Metaverse

/ˈmɛtəvɜːs/

noun COMPUTING

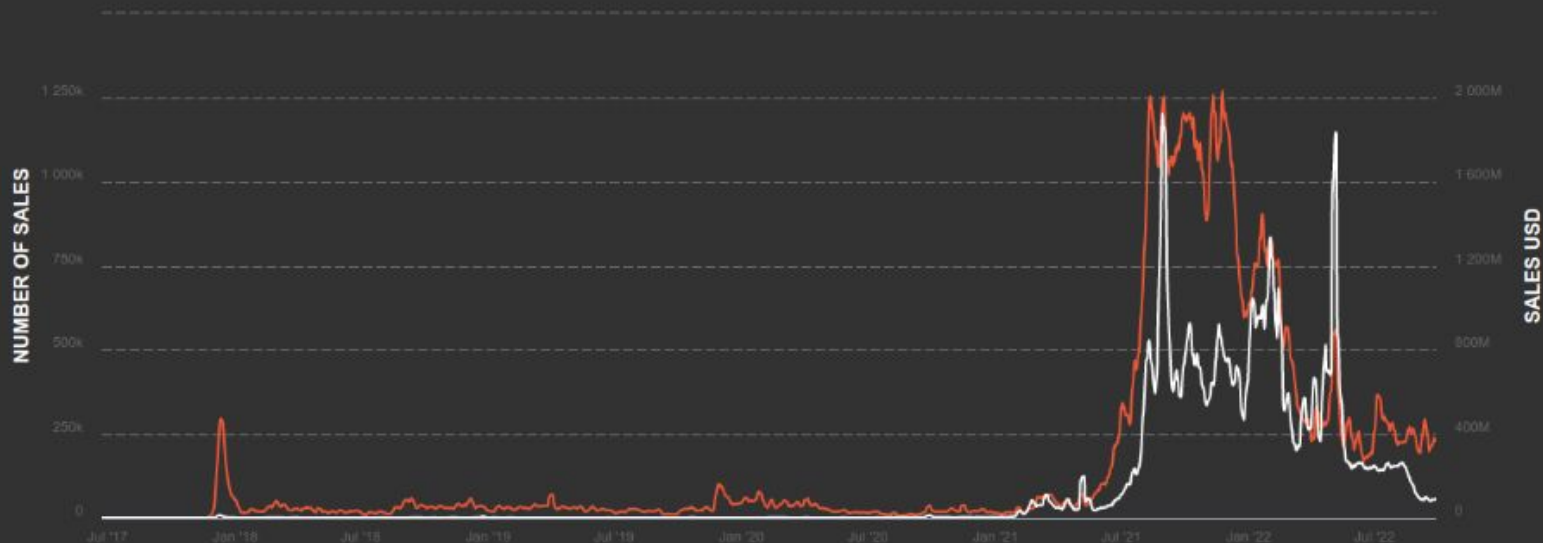
- A public digital space featuring unique, customisable avatars representing individual users,
- Where digital ownership ranges depending on how decentralized the platform is,
- where you can engage with other users,
- interact with elements of the digital world, and
- share experiences with others based on the platform



Virtual land in nemesis

Exponential Growth of NFT Market

Number of sales · Sales USD · All · Weekly



Number of sales

230K

1209342.11%

Sales USD

US\$90M

8791319.80%

Average USD

US\$390

626.91%

Active market wallets

74K

927312.50%

Primary Sales

107K

595305.56%

Secondary sales

123K

12259300.00%

Primary sales USD

US\$5M

514228.18%

Secondary sales USD

US\$85M

127738418.64%

Unique buyers

51K

639612.50%

Unique sellers

38K

1908500.00%

The boom in NFTs has led to a spike in crime around digital collectibles.

NFT



ART THEFT

More than \$100m worth of NFTs stolen since July 2021, data shows

Fake Bored Ape NFTs Outsell Their Original Versions, Calls NFT Authenticity to Question

Marketplace suspends most NFT sales, citing 'rampant' fakes and plagiarism

NFT Insurance



TOKEN PROTECTION

Token theft equates to loss of ownership



INHERITANCE PROTECTION

Contingency plan for release of assets to beneficiaries



PROTECTED TECHNOLOGY

Protection that we can stand behind



VALUATION

Appraisals and qualified valuation of digital assets



AUTHENTICATION

Authenticated assets maintain market value



DISASTER RECOVERY

Not your keys, not your NFT



ASSET STORAGE

Possess the media you own

Insurance pricing model

Given a asset A,

Total Loss (L) = Total Claims (N) x Average Claim Severity (S) / Risk Exposure (e)

The technical price π (or: pure/risk premium) then follows as:

$$\pi = \mathbb{E}\left(\frac{L}{e}\right) \stackrel{\text{indep.}}{=} \mathbb{E}\left(\frac{N}{e}\right) \times \mathbb{E}\left(\frac{L}{N} \mid N > 0\right) = \mathbb{E}(F) \times \mathbb{E}(S)$$

assuming independence between the frequency and the severity component of the premium.

For an NFT insurance, N (No. of claims) = 0/1 only in the given year

And S (Claim severity) = min(x% of NFT price as declared in policy, Maximum insured amount)

Thus, L (Total loss amount) = 0/S

$\therefore \pi$ (pure/risk premium) = $E(\text{claim is made in a given year}) \times \text{Insured NFT price}$

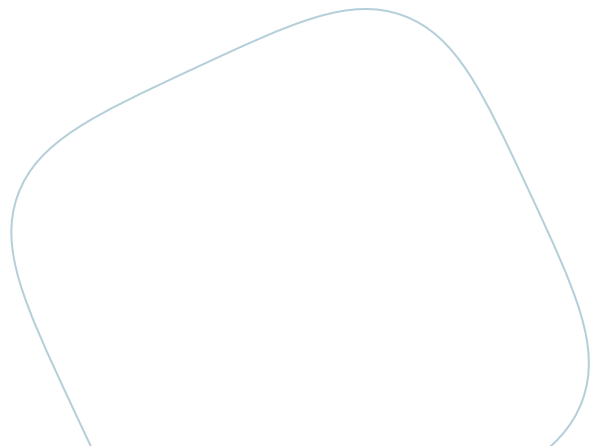
$E(\text{claim is made in a given year}) = P(\text{claim is made in a given year})$ since $\text{maxClaim}=1$

Working on 1st Challenge

– The Underwriter's Dilemma

Underwriters face the problem of lack of data and volatility related to NFT market that makes it difficult to calculate a premium and coverage price that would keep the balances green.

We intend to train a ML model that calculates NFT Valuation at the time of insurance proposal.



The background of the slide features a light blue field with numerous gold coins floating at various angles. Each coin is depicted with a 3D effect, showing a red-orange shadow beneath it. The coins are scattered across the frame, with some showing different symbols like a checkmark, a dollar sign, and a Bitcoin logo. In the center, a large, rounded pink rectangle contains the text "NFT Valuation" in white, bold, sans-serif font.

NFT Valuation

Previous Work

Mapping the NFT revolution: market trends, trade networks, and visual features

The results of this paper include the statistical properties of the market, a network of interactions between traders (linked by buyer and seller), and a clustering of objects by visual features and collections. The paper also proposes a linear regression model with features based on these results to predict NFT prices.

Group 1: Network Centrality	Group 2: Visual Features	Group 3: Sale History
<ul style="list-style-type: none">- Degree centrality of seller- PageRank centrality of seller- Degree centrality of buyer- PageRank centrality of buyer	Five PCA components extracted from the AlexNet vector of the NFT.	<ul style="list-style-type: none">- Median price of primary and secondary sales made in the collection of interest.- The prior probability of secondary sale.

Results

β coefficients

Feature	All	Art	Collectible	Games	Metaverse	Utility	Other
const.	-0.029	0.030	-0.086	-0.181	0.210	2.054	0.149
k_{buyer}	-0.018	0.022	-0.032	-0.132	-0.078	-0.010 [•]	-0.207
k_{seller}	-0.166	-0.211	0.000	0.026	0.166	0.198 [•]	-0.347
PR_{buyer}	0.129	0.077	0.162	0.317	0.206	-0.241 [•]	0.336
PR_{seller}	0.302	0.367	-0.031	-0.066	0.009 [•]	-0.382	0.459
$presale$	0.029	-0.041	0.079	0.023	0.046 [•]	0.465	0.251 [•]
$medianprice$	0.769	0.711	0.970	0.815	0.436	0.478	0.687
$visPCA_1$	0.098	0.153	0.049	0.174	0.175	-1.136	0.021
$visPCA_2$	-0.120	-0.130	-0.044	-0.064	-0.669	-0.817	-0.181
$visPCA_3$	0.019	0.027	0.063	0.203	0.112 [•]	-1.292	-0.037 [•]
$visPCA_4$	0.040	0.028	-0.003 [•]	0.130	-0.018 [•]	-0.911	-0.116
$visPCA_5$	0.063	0.018	0.276	0.102	0.296	0.071 [•]	0.301
#NFTs	407,549	251,369	69,015	78,848	2,693	314	5,297
#Collections	3307	114	73	48	12	6	3054
R^2_{adj}	0.6	0.589	0.709	0.535	0.408	0.562	0.44

Previous Work

The NFT Hype: What Draws Attention to Non-Fungible Tokens?

This paper focuses on utilizing vector autoregressive models (VARs) to show that core cryptocurrencies, namely Bitcoin (BTC) and Ether (ETH) draw the most attention towards predicting future NFT price.

This team utilizes the S&P 500, google search trends, and the prices of cryptocurrencies as indicators for future price of an NFT. This team highlights that google search trend data is associated with major cryptocurrency returns and NFT collections. In addition to VARs this team uses wavelet coherence techniques to investigate co-movement between cryptocurrency returns and NFT levels of attention.

The results of this paper show that there is no significant relationship between Ether returns and attention to NFTs but there is a relationship between Bitcoin and the prediction of an NFT.

Previous Work

TweetBoost: Influence of Social Media on NFT Valuation

This paper aims to answer two main questions:

- a) What is the relationship between user activity on Twitter and price on OpenSea?
- b) Can we predict NFT value using signals obtained from Twitter and OpenSea, and identify which features have the greatest impact on the prediction?

Kapoor et al. concluded that in adding Twitter data to their feature set they were able to increase the accuracy of their model by 6% when compared to a model only using data from NFT platforms (such as OpenSea).

Feature Set Used	Binary Accuracy	Binary F1	Ordinal Accuracy	Ordinal Index
Twitter	83.75	82.00	67.03	0.3645
OpenSea	-	-	63.22	0.3882
Twitter + OpenSea	-	-	69.33	0.3423

Previous Work

TweetBoost: Influence of Social Media on NFT Valuation

This paper aims to answer two main questions:

- a) What is the relationship between user activity on Twitter and price on OpenSea?
- b) Can we predict NFT value using signals obtained from Twitter and OpenSea, and identify which features have the greatest impact on the prediction?

Kapoor et al. concluded that in adding Twitter data to their feature set they were able to increase the accuracy of their model by 6% when compared to a model only using data from NFT platforms (such as OpenSea).

Model	Ordinal Accuracy	Ordinal Index
Logistic Regression	60.23	0.4049
SVM	63.90	0.3880
Random Forest	66.31	0.3459
LightGBM	68.84	0.3441
XGBoost	69.33	0.3423

Problem Statement



Our objective is to develop a machine learning model capable of –

- outperforming previous models in accurately predicting the price of NFTs.
- is applicable on new blockchain platforms that it has not been trained on.
- is effective in predicting prices for NFT collections that have recently been minted and are unfamiliar to the model.

Features

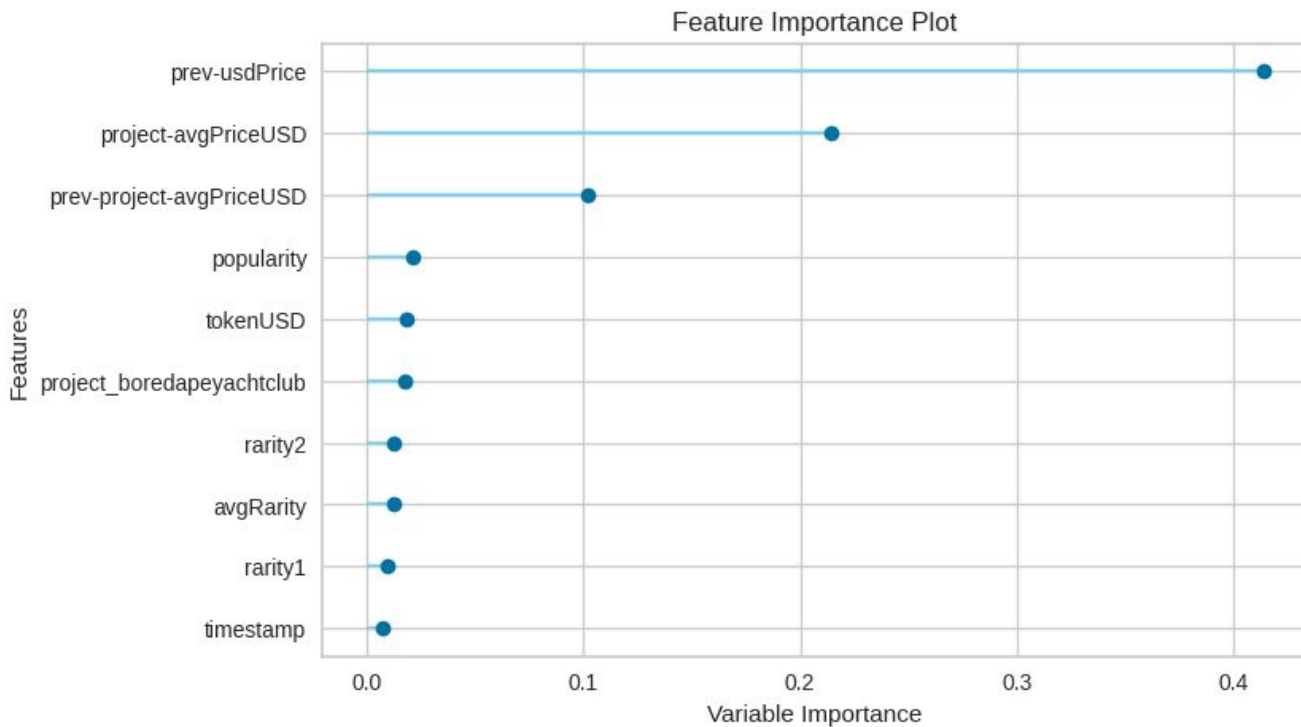
As a regression problem for multiple NFT collectibles

Training on sales data in 15 NFT Collection of varying popularity over a year based on:

- **Timestamp**
- **NFT Features**
 - 'avgRarity', 'rarity1', 'rarity2',
 - 'prevUSDPrice', 'tokenUSDPrice', 'holdTime',
- **Network centrality**
 - 'sellerAssetMarketCount', 'sellerAssetReceiveCount'
- **Current market state**
 - NFT Collection Statistics
 - NFT Market Statistics
 - Platform Market Statistics
- **Previous market state**
 - NFT Collection Statistics
 - NFT Market Statistics
 - Platform Market Statistics
- **Social Media Score**

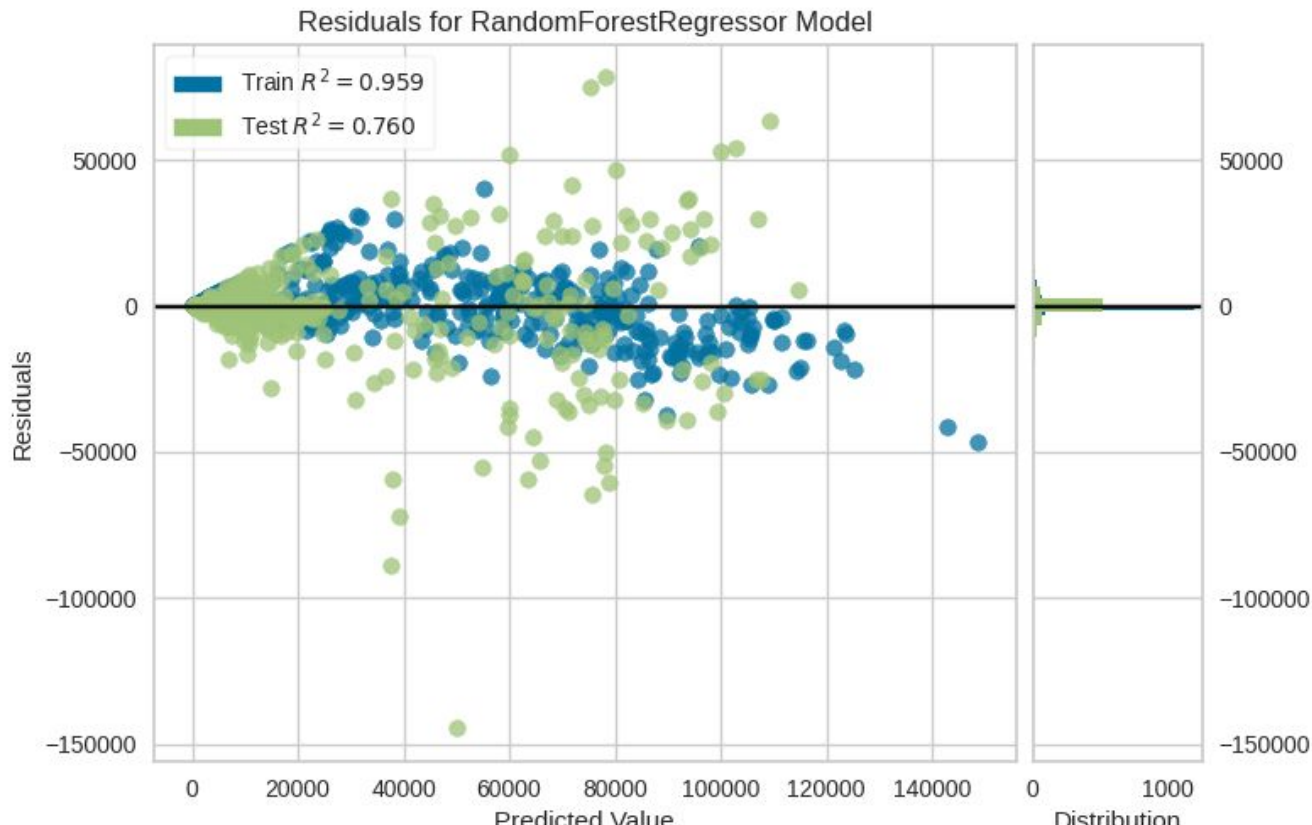
Features

As a regression problem for multiple NFT collectibles with project tag



Features

As a regression problem for multiple NFT collectibles with project tag



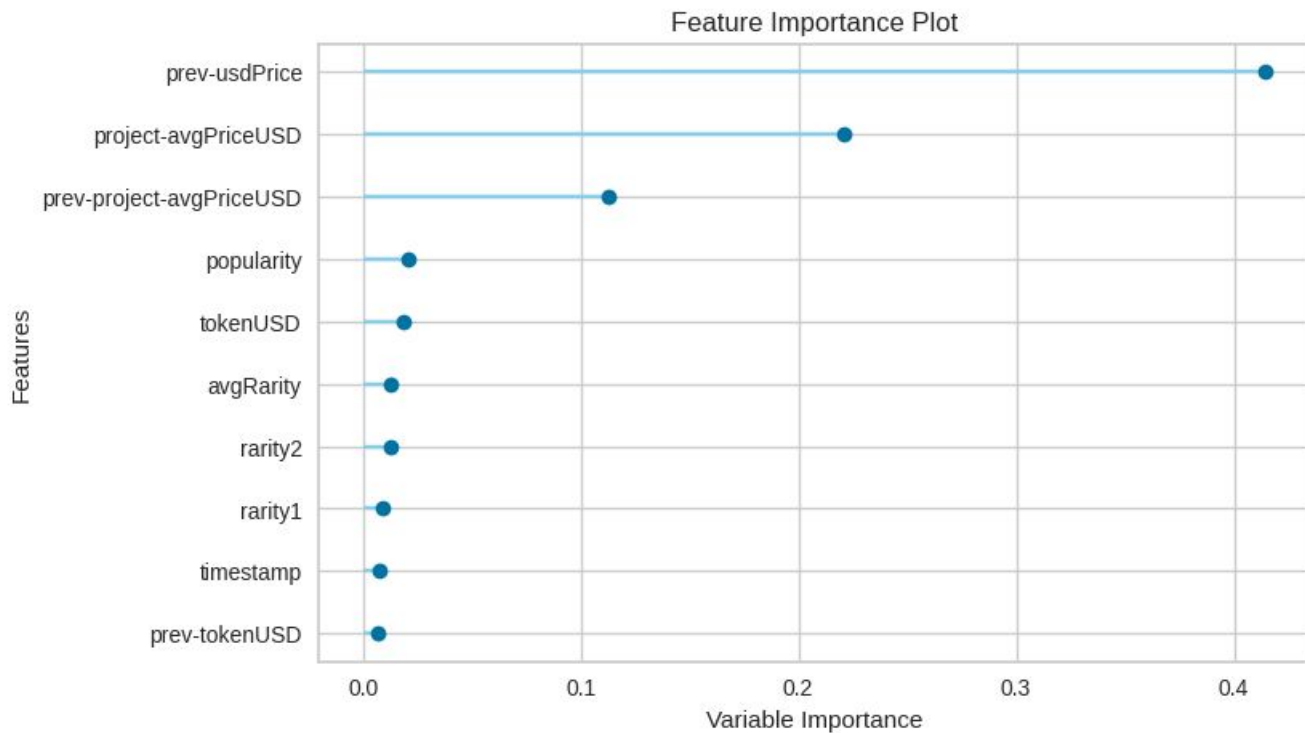
Result

As a regression problem for multiple NFT collectibles

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE
rf	Random Forest Regressor	5997.4385	201805385.7719	13955.3142	0.7111	1.0119	67.9077
et	Extra Trees Regressor	5973.4047	201045204.2869	14003.7704	0.7107	1.0072	63.4687
br	Bayesian Ridge	6691.3999	209475763.9825	14167.7499	0.7011	1.0883	66.5887
gbr	Gradient Boosting Regressor	6292.5302	212557638.8201	14271.2010	0.6986	1.0521	70.6831
llar	Lasso Least Angle Regression	7200.0024	211505373.9534	14253.4195	0.6967	1.1853	69.8021

Features

As a regression problem for multiple NFT collectibles without project tag



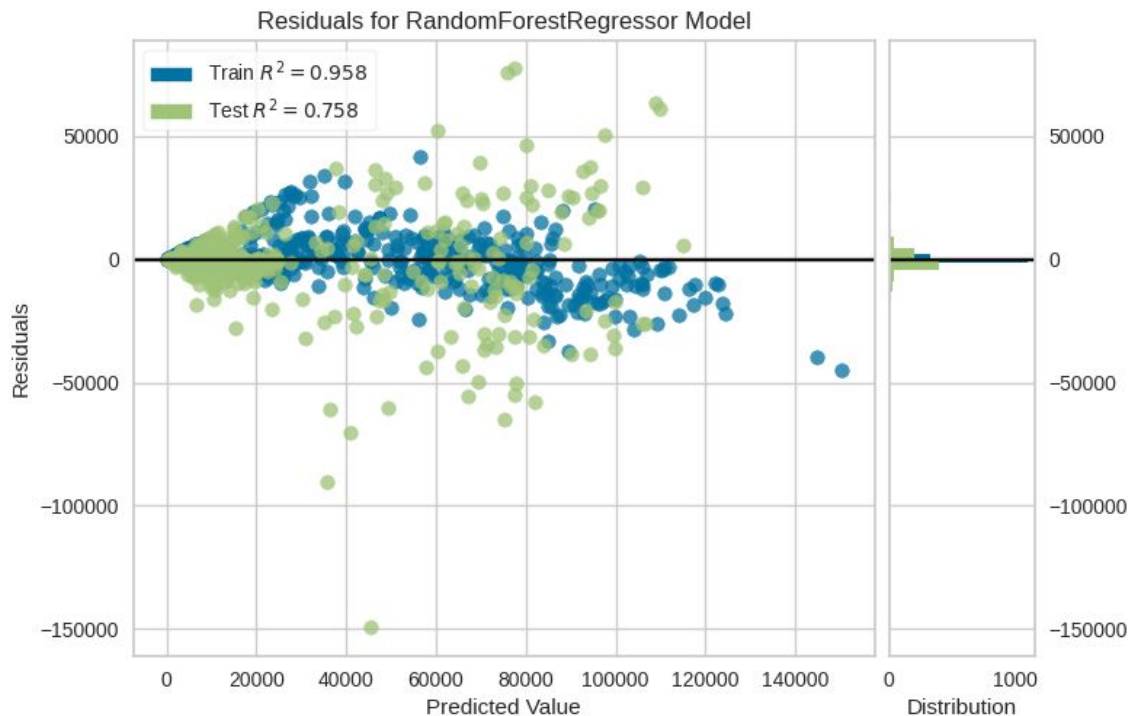
Result

As a regression problem for multiple NFT collectibles without project tag

Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	
rf	Random Forest Regressor	5985.2140	202458102.2987	13969.2941	0.7105	1.0102	68.3207
br	Bayesian Ridge	6691.3999	209475763.9774	14167.7499	0.7011	1.0883	66.5887
et	Extra Trees Regressor	6012.6075	205992145.0616	14183.2881	0.7005	1.0054	63.8521
gbr	Gradient Boosting Regressor	6297.1944	214085711.2852	14322.2277	0.6961	1.0496	70.4477
llar	Lasso Least Angle Regression	7180.3034	212222887.3370	14277.6415	0.6957	1.1564	70.8093

Features

As a regression problem for multiple NFT collectibles without project tag



Drawbacks & Constraints

As a regression problem for multiple NFT collection

- ❑ Model is not able to forecast price or other market statistics in advance of couples of days.
Can only predict next day price.
- ❑ Needs to retrain model on new sales data every day-week.

Possible Improvements

- Use of social indicator features like twitter dataset
- Use of AI models
 - to detect NFT wash trading





Thanks!