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

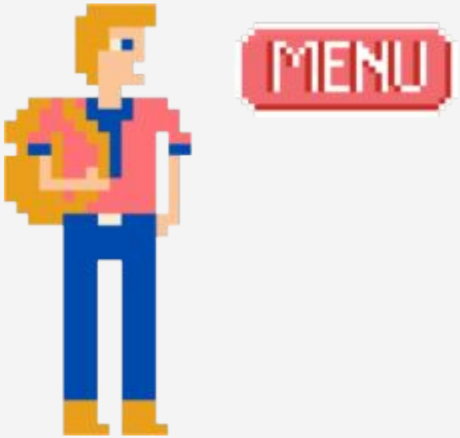
PROBLEM STATEMENT

What to do?

03

P1: NFT VALUATION

NFT Price Appraisal in Turbulent Market



04

P2: RISK PREDICTION

Calculating risk for an NFT

05

FUTURE WORK

What Next?

Pretext | NFTs

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

Problem Statement

In this project, we aim to design an insurance framework for metaverse objects like art, collectibles, virtual land and avatars using blockchain.

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:

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

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

∴ π (pure/risk premium) = E(claim is made in a given year) ✕ Insured NFT price

E(claim is made in a given year)= P(claim is made in a given year) since 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
- Risk Prediction

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**
- Degree centrality of seller - PageRank centrality of seller - Degree centrality of buyer - PageRange centrality of buyer	Five PCA components extracted from the AlexNet vector of the NFT.	- 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
$p_{presale}$	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
vis_{PCA_1}	0.098	0.153	0.049	0.174	0.175	-1.136	0.021
vis_{PCA_2}	-0.120	-0.130	-0.044	-0.064	-0.669	-0.817	-0.181
vis_{PCA_3}	0.019	0.027	0.063	0.203	0.112•	-1.292	-0.037•
vis_{PCA_4}	0.040	0.028	-0.003•	0.130	-0.018•	-0.911	-0.116
vis_{PCA_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?

While answering this question, the paper seeks to create one of the first NFT datasets consisting of both OpenSea and Twitter data. Using both a Binary and Multi-classification model to first predict whether or not the NFT will be profitable and then classifying the profitable NFTs into varying price brackets. 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). This paper gives insights into additional training strategies and features for use within our predictive model.

Aggregated Data Dictionary

Variable	Description
opening_date	Date of which information is being pulled.
average_volume_quote _day	Average price of the NFT as of opening_date.
unique_token_ids_sol d_count	The number of NFTs from a given collection sold in one day.
Relative Search Volume	Relative google search volume for collection name on a scale from 0-100
Events	-1,0,1 indicating bad news, no news, and good news respectively
Gas	A measure of network traffic, which indicates the transaction fee of purchase

Variable	Description
ETH_USD	Closing price of ETH token.
BTC_USD	Closing price of Bitcoin.
GC=F	Closing price of gold.
^GSPC	Closing S&P value.
^DJI	Closing Dow Jones value.
^NDX	Closing Nasdaq 100 value.
MSFT	Closing Microsoft stock price.
AAPL	Closing Apple stock price.
NFLX	Closing Netflix stock price.
TSLA	Closing Tesla stock price.

Ongoing Work

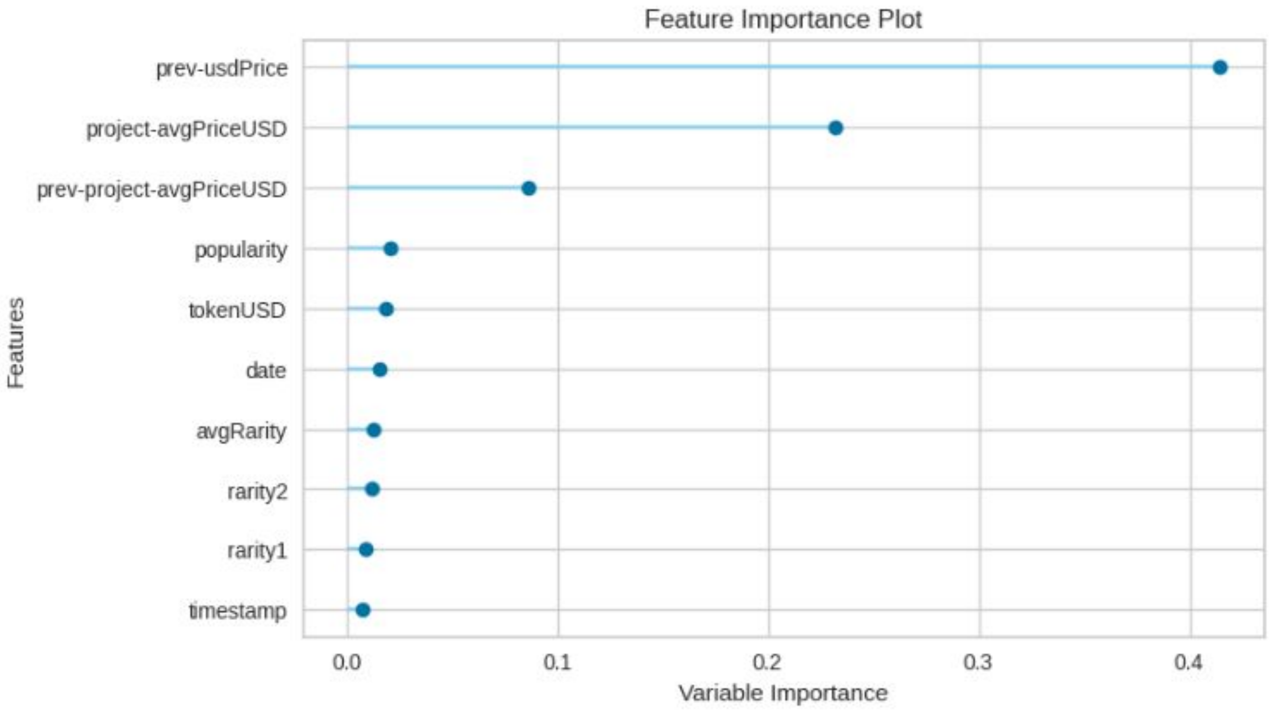
As a regression problem for multiple NFT collectibles

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
  - Collectibles Statistics
  - NFT Market Statistics
- **Previous market state**
  - NFT Collection Statistics
  - Collectibles Statistics
  - NFT Market Statistics
- **Social Media Score?**
-

Features

As a regression problem for multiple NFT collectibles



Result

As a regression problem for multiple NFT collectibles

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE
rf	Random Forest Regressor	5977.0597	203107664.0332	13987.4465	0.7096	1.0099	68.7023
et	Extra Trees Regressor	5981.0767	200844395.4329	13998.6279	0.7089	1.0055	64.4779
br	Bayesian Ridge	6681.5030	209501762.6255	14175.5943	0.7010	1.1083	66.8981
ridge	Ridge Regression	7299.8645	211657590.3271	14262.6113	0.6964	1.1762	69.8826
llar	Lasso Least Angle Regression	7196.4819	211914786.6784	14268.2187	0.6961	1.1610	70.2268
gbr	Gradient Boosting Regressor	6275.7877	214627243.7834	14327.6436	0.6957	1.0509	71.1503
lasso	Lasso Regression	7139.1798	212246669.3191	14278.9015	0.6955	1.1554	69.3195
lr	Linear Regression	7316.7053	212265513.9632	14283.9132	0.6954	1.1756	69.6260
en	Elastic Net	6987.9887	213137925.4184	14305.2964	0.6953	1.1539	69.4086
xgboost	Extreme Gradient Boosting	6336.8217	222409528.0000	14669.2212	0.6825	1.0409	60.0059
lightgbm	Light Gradient Boosting Machine	6379.2681	225673288.7525	14834.1002	0.6718	1.0321	70.4574

Ongoing Work

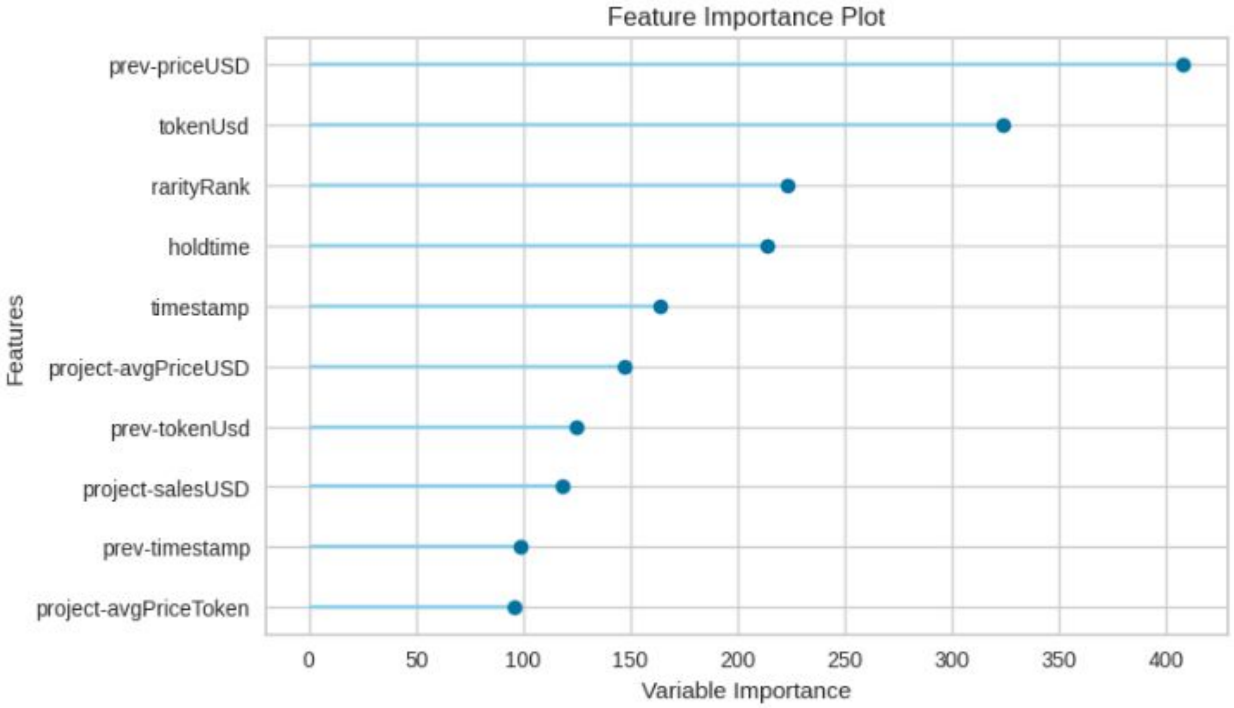
As a regression problem for multiple virtual land

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

- **Timestamp**
- **NFT Features**
- 'rarityRank',
- 'prevUSDPrice', 'tokenUSDPrice', 'holdTime','number of sales'
- **Network centrality**
- 'sellerAssetMarketCount',' sellerAssetReceiveCount'
- **Current market state**
  - NFT Collection Statistics
  - Metaverse Statistics
  - NFT Market Statistics
- **Previous market state**
  - NFT Collection Statistics
  - Metaverse Statistics
  - NFT Market Statistics
- **Social Media Score?**

Features

As a regression problem for multiple virtual lands



Result

As a regression problem for multiple virtual world

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
lightgbm	Light Gradient Boosting Machine	223.7992	1491094.6353	961.5441	0.6410	0.1341	0.0593	0.5950
knn	K Neighbors Regressor	322.8394	2411250.6328	1291.7156	0.4054	0.1966	0.0868	0.1180
gbr	Gradient Boosting Regressor	261.9099	2049152.9595	1206.9167	0.3210	0.1358	0.0693	1.1500
rf	Random Forest Regressor	232.0854	2297455.5312	1321.1870	0.2104	0.1376	0.0532	2.9300
et	Extra Trees Regressor	224.7943	2656168.3867	1402.4327	0.0406	0.1307	0.0476	1.3370

Drawbacks & Constraints

As a regression problem for multiple NFT collection

- Not able to forecast price or other market statistics in advance of couples of days.
- Can only predict next day price.
- Retrain model every day-week.

NFT Risk Prediction

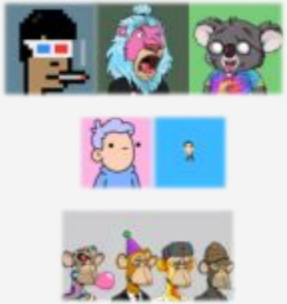
NFT Pipeline

Application interfaces and middleware

Off Blockchain

On Blockchain

Users' content



User generated content in the format of jpeg, gif, videos, etc.

Identity and wallet services

To create or mint NFTs, users first need to set up a crypto address and wallet with private key signatures.

Marketplaces

With that crypto address, users can use marketplaces or aggregators that offer services to mint their digital content into NFTs.

Blockchain network APIs

These marketplaces often interact and communicate with the blockchain networks through numerous API services

Networks

Using a smart-contract enabled blockchain, these transactions are recorded with a unique and immutable ID along with all relevant data associated with the NFT

NFT Architecture

Token Standard	Metadata	Storage	Digital Link	IP Rights	Smart Contract
A set of rules for issuing uniquely identifiable tokens on a blockchain, like ERC-721 on Ethereum	A JSON doc with data that describes an NFT which lives outside the actual NFT and is located by a URI.	Software crypto wallets and cold hardware wallets provide access to underlying assets of the NFTs	NFTs often do not contain the image or video as storing digital data on blockchains is slow and inefficient	Clauses on IP rights such as copyright and ownership rights between creators and buyers	if/then and when statements written as codes that store data and executed upon meeting certain conditions
A standard interface for NFTs that provide basic functionality to track and transfer NFTs separately	Provides users with key information on the NFT such as names, descriptions, traits and links to hosted files	Users view and approve NFT transactions using crypto wallets protected by their seed phrases.	Acts as a mutable pointer to assets located off-chain (i.e. IPFS) and associates NFTs with URIs	Determines the authority of creators and buyers to use the underlying artwork within an NFT	Handles transfers, verifies ownership and authenticity whilst enabling the digital programmable aspect of an NFT

Future Plan

- Train the model for NFT valuation and risk factor with satisfactory results.

Thereafter, work will be done to complete the insurance framework including

  - Application procedure
  - Claim process
  - Claim review process

- Use of AI models
  - to prevent NFT plagiarism
  - to detect NFT wash trading

Thanks!