Vrije Universiteit Amsterdam

Universiteit van Amsterdam

Master Thesis

Leveraging data to unravel the chaos of NFT markets

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A thesis submitted in fulfillment of the requirements for the joint UvA-VU Master of Science degree in Computer Science

September 4, 2023

"I am the master of my fate, I am the captain of my soul"
from Invictus*, by William Ernest Henley*

Abstract

This thesis investigates the factors impacting daily sales of Non-Fungible Tokens (NFTs), a developing area in the market of digital assets. Our approach involves characterization and identification of models encompassing both global and local feature importance. Various regression methods are utilized to determine the feature importance and select the predictive features effectively by employing the Recursive Feature Elimination (RFE) technique. Moreover, this study explores the correlation between search interest and weekly NFT sales and vice versa, to comprehend how public interest impacts the NFT market. Lastly, anomalies in daily sales are detected and analysed using STL Decomposition and local feature importance method called SHAPely. Our analysis indicates that intrinsic sales attributes and trade profits drive daily NFT sales. The study reveals a significant impact of positive sentiment on Ethereum volatility and NFT sales, indicating the potential sentiment-driven nature of the crypto and NFT markets. The primary factors responsible for positive and negative anomalies are the intrinsic sales factors like weekly sales average and lagged sales. Additionally, external factors like daily supply of NFTs, Ethereum price and trade profits have a varying degree of influence on both anomalies. These findings suggest that positive sentiment plays a crucial role in shaping the dynamics of the crypto and NFT markets. Intrinsic sales variables have a more profound impact on daily sales as opposed to external factors mentioned.

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Introduction

Non-Fungible Tokens (NFT) are a breakthrough innovation that have emerged from the blockchain ecosystem. These digital assets have piqued the interest of investors, creators, and collectors alike. There are several interpretations of what NFTs may indicate. On the one hand, NFTs are regarded as a critical component of Metaverse and Web3.0, as well as a revolution in the marketing and monetization of digital goods (2). Critics, on the other hand, view them as a celebrity-fueled craze and a tool to launder money and evade taxes (3).

NFTs have swiftly gained popularity, captivating the world with their ability to authenticate and prove ownership of digital creations. The digital content is tokenized and unique information about the owner, creator and transactions are stored on the blockchain, mostly Ethereum (4). Blockchain is a distributed ledger which comprises of data packages called blocks, where each block contains transactions. It can be expanded with more blocks, transforming the system into a distributed ledger. It is known for it's decentralisation, anonymity and persistence (5). Ethereum is a decentralized blockchain with programmable smart contract capabilities (6).

CryptoKitties, which debuted in late 2017, was one of the first NFT ventures to garner widespread notice. CryptoKitties helped popularize NFTs, resulting in the establishment of various NFT markets, such as OpenSea (in 2017), where users could purchase, sell, and trade NFTs (7). The later years saw steady growth in the marketplace. NFT marketplaces started to diversify, and platforms like Rarible and Mintable emerged. Gaming also became a popular use case for NFTs, with games like Decentraland and Axie Infinity leveraging blockchain technology. NFTs began to be used to represent ownership of digital assets like unique digital artwork (8), domain name (9), event coupons (10), degree certificates (11), music royalties via NFTs (12), digital collectibles (13) and so on.

On March 2021, Beeple's (the artist's) collage style NFT titled "Everydays: The First 5000 Days" was sold for $69.3 million (14) (15). The NFT market started showing a meteoric in terms of popularity and revenue influx in 2021. While NFTs had existed prior to 2021, it was during this period that they captured mainstream attention and witnessed a surge in adoption (16). NFTs have opened up new economic opportunities for artists, allowing them to commercialize their digital creations in novel ways. Artists, for example, can now earn royalties when their NFT is sold or traded on the secondary market (resales). This gives artists a steady income and motivates them to keep creating and sharing their work (17). However, The NFT Market saw a massive decline of 25% between 2022 Q1 and Q2 (18). It later declined sharply in terms of USD traded and resale profit by the end of the year (19) (20). NFTs sold for millions of dollars during the bubble have been left with very little value now (21) (22).

The NFT hype was fueled by staggering sales figures and celebrity endorsements, creating a speculative bubble that captivated the global financial and cultural landscape. However, the NFT market experienced a subsequent bubble burst, leading to a sharp decline in sales and valuations (23). The dramatic ups and downs in the NFT landscape highlight the inherent volatility and risk associated. This volatility potentially represents market manipulations, trends, and reactions to external events. The current research landscape of studying the daily working of NFT market remains largely unexplored and is pivotal for stakeholders to learn better investment practices.

Given the nascent stage of the industry and the high levels of interest and investment, it is critical to establish an empirical understanding of the mechanics and factors that drive NFT sales. This research will bridge the knowledge gap by investigating these relationships, while providing a clearer understanding of the ever changing and unpredictable market.

1.1 Research Question

This research aims to answer the following question(s):

How do external market forces and overall public opinion together shape the trends and patterns in NFT sales?

1. What are the most important factors driving NFT sales?
2. How to identify factors impacting sales across different time windows?
3. How do market sentiment, crypto volatility and NFT market (Sales) interact with each other?
4. To what extent could anomalies in daily NFT sales be attributed to specific internal or external factors?

To accomplish this, the study will draw upon extensive research of NFT market variations to highlight elements which impact the NFT ecosystem. The study will also provide a comprehensive analysis of the NFT marketplace, leveraging advanced techniques from the realms of machine learning and data driven methods. Additionally, sentiment around the market and its implication are also analysed. By understanding the nature of these factors, we can safeguard the interests of artists, collectors, and investors, while fostering a healthy and sustainable NFT ecosystem.

Rest of the research is organized as follows: Section 2 contains the background necessary for the study. Section 3 summarizes literature review procedure and related work for the study. Section 4 includes the methodologies followed for this thesis. Section 5 entails the experiment design and results obtained, followed by Section 6 which has a concise discussion. Section 7 concludes the thesis and mentions scope for future work.

2

Background

This section provides the necessary background knowledge required for remainder of the study. Following an explanation of the technical components of Blockchain technology and NFTs, cryptocurrency and token economics are presented. The section concludes with an overview of volatility analysis.

2.1 Blockchain

Blockchain is a public ledger comprised of a chain of data packages called blocks, where each block is a set of transactions. The chain can be expanded with the addition of new blocks (1). Each block consists of a timestamp, reference to the previous (parent) block - called *hash value*, a random number to verify the hash - called *nonce* (24).

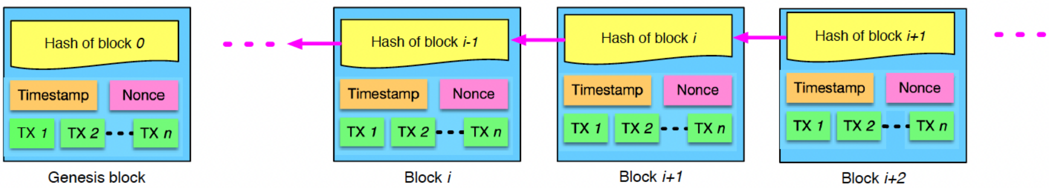

Figure 2.1: Example of a Blockchain (1)

The following are the key characteristics of a blockchain:

- **Decentralisation** : In traditional transaction systems, there is a centralised authority to monitor and enable transactions. Decentralization in blockchain refers to the distribution of control and authority across the peer-to-peer network, as opposed to being concentrated in a single entity or a centralized system. There is no third party involved, thus making it secure. This makes the system less prone to failure, organised and fault tolerant.
- **Auditability** : Every blockchain transaction is recorded using a timestamp and hash. Priors records could be easily traced using these fields.

- **Immutability** : After being recorded on the blockchain network, transaction data cannot be changed, manipulated or removed. The transaction's validity is checked before recording it on the network. The tamper-resistant ledger now establishes a framework that promotes high levels of security and trust.
- **Consensus** : Every blockchain has a consensus to help the network to make quick and unbiased decisions. Consensus is a decision-making algorithm for the group of nodes active on the network to reach an agreement quickly and faster and for the smooth functioning of the system. Nodes might not trust each other but they can trust the algorithm that runs at the core of the network to make decisions. There are many consensus algorithms available each with its pros and cons. Every blockchain must have a consensus algorithm otherwise it will lose its value.

2.2 Cryptocurrency

Bitcoin is a peer-to-peer electronic cash system, which is a type of digital or virtual currency (5). It is a cryptocurrency that uses cryptographic trust for secure transactions, verification of asset transactions and control over creation of new units. It was invented in 2008 by a person/group of people under the name Satoshi Nakamoto. Ethereum is another decentralised blockchain whose native currency is *Ether*(6). Ether is second to bitcoin in terms of market capitalization (25). The essential building blocks of Ethereum applications are smart contracts (26).They are immutable computer programs stored on the blockchain that are used to generate digital tokens that can represent proof of membership, assets, currency, and so on . Smart contracts are written in Solidity, a low-level, stack based byte-code language (27). Unlike a distributed ledger, Ethereum is a distributed state machine. The state is a data structure comprising of account details and the machine state. The aforementioned components reside on the Ethereum Virtual Machine (Figure 2.2).

As mentioned in the previous section, consensus algorithms are pivotal to a Blockchain network. It is a technique through which all peers in the Blockchain network achieve a consensus on the current state of the distributed ledger. A popularly used consensus algorithm is *Proof of Work (POW).* Blockchain traditionally uses Proof of Work algorithm to confirm transactions and add new blocks to the system. A new block is added when a miner successfully solves a complicated mathematical puzzle. To compensate the miners for using computational resources to validate transactions, every transaction has a *Gas fee (gwei).* Gas is the unit that measures the amount of computational effort required to

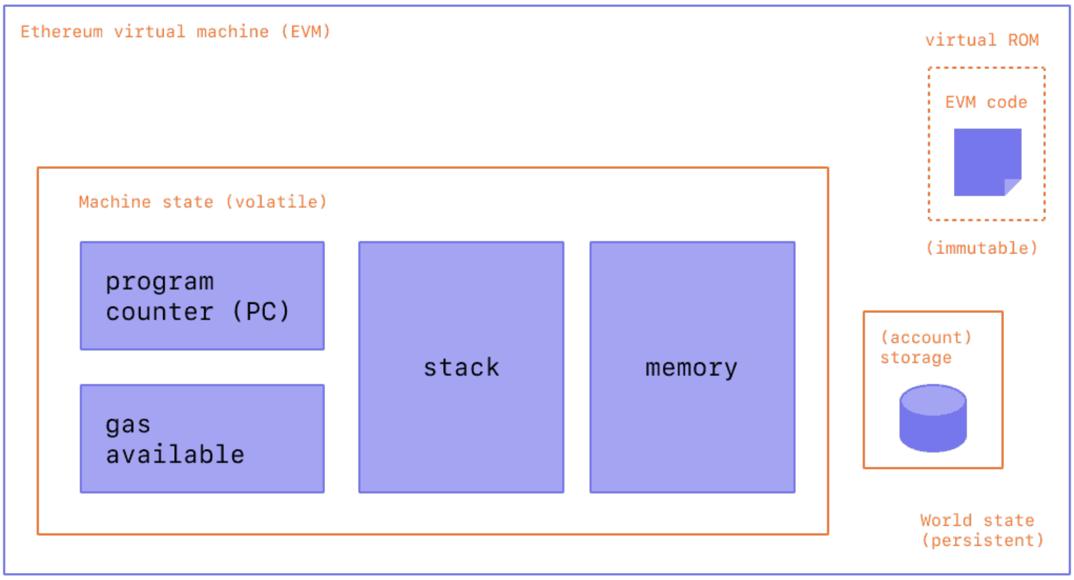

Figure 2.2: Ethereum Virtual Machine
(28)

execute specific operations on the Ethereum network. Gas prices fluctuate based on factors like network congestion, processing speed and transaction throughput.

Blockchain networks can experience congestion when the volume of transactions exceeds their scalability. This results in users having to compete for transaction processing through payment of higher gas fees. Improved scalability in blockchain networks enables them to handle higher transaction volumes without congestion, thereby helping to maintain lower gas fees. Notably, Ethereum network and other blockchains have limited transaction processing capacity per second, which necessitates higher gas fees during network congestion. This is because miners prioritize transactions with higher fees.

During periods of heightened network activity, a scenario may arise wherein a competition for resources, known as a bidding war, occurs among users who are motivated to pay increasingly exorbitant gas fees to guarantee the prompt processing of their transactions. Scalability is frequently evaluated based on the transaction throughput, which is the total number of transactions that can be handled by a network in a second. In instances where the transaction throughput is low, such as with earlier versions of Ethereum, the network's capacity to manage transactions is restricted, resulting in users having to pay elevated gas fees to prioritize their transactions.

2.3 Non-Fungible Tokens

A Non-Fungible Token (NFT) is a cryptographic token used to verify ownership of goods such as digital art, photography, and gaming merchandise. Typically, NFTs are generated, exchanged, and stored on the Ethereum blockchain. The actual digital asset is not stored on the blockchain; rather, it stores a link to the actual digital asset. Ethereum provides a secure, decentralized and tamper-proof platform for NFTs. Smart contracts allow the creation of unique token, which are then used to represent digital assets like art, music, virtual collectibles and so on.

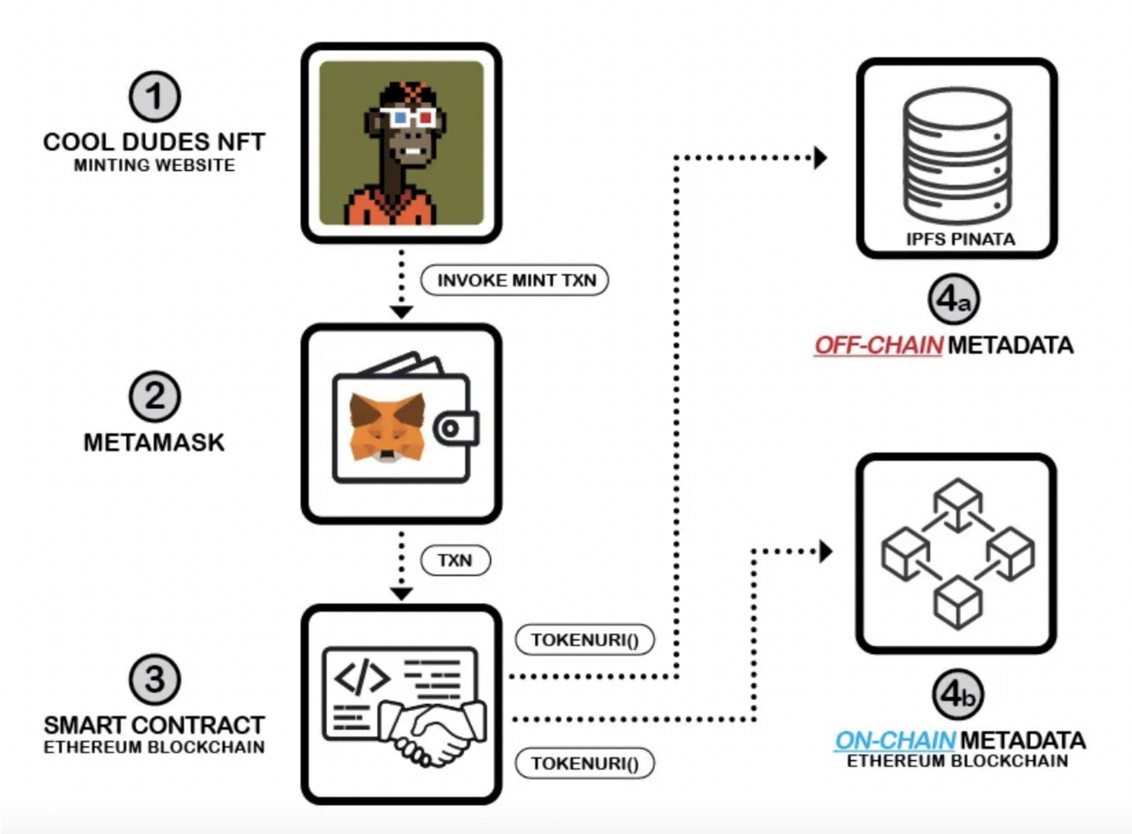

Figure 2.3: NFT Project on Ethereum
(29)

The introduction of the ERC-721 token standard in 2017 marked the beginning of the age of NFTs (30). These standards define how NFTs are minted (produced), transferred, and burnt (destroyed), as well as how to access token information. ERC-721 creates NFTs for single assets. The token has capabilities to record transaction history and register copyright ownership. Royalty payments can be initiated with resale of NFTs due to it being able to record transaction history. Figure 2.3 illustrates the architecture of an NFT project on Ethereum. The first component is a minting website, where users create/host NFTs. A wallet is then linked to the blockchain for further transactions. Methods like `tokenuri()` are then required to prepare for interaction with a smart contract that will mint the NFTs. The smart contracts also reside on the Ethereum blockchain.

While NFTs are traded using cryptocurrency such as Ether and have crypto-like properties, they are very different. Cryptocurrencies have some asset like properties, but are not exactly assets. But Non-fungible tokens are pure assets and are unique in nature.

2.4 Volatility

Volatility is a statistical gauge of the degree of variation in the value of an asset over time. The magnitude of volatility conveys the extent to which price variations occur within a short time frame, with low volatility indicating stability. Bitcoin and Ethereum, the two most well-known cryptocurrencies, have exhibited significant fluctuations since their inception. Cryptocurrencies, being a nascent financial asset, exhibit price fluctuations primarily driven by speculation, sentiment, and news events unlike traditional assets.

2.5 Search interest in the NFT market

There has been a notable surge in the NFT market in 2021. This surge has been marked by an interdependent relationship between the increase in sales and the growth in hype. High-profile sales, such as artwork selling for millions of dollars, has garnered a lot of attention (31). This, in turn, has fueled even more interest and speculation in the NFT space. The media attention and associated public intrigue have driven even higher sales, as both experienced investors and novices seek to capitalize on what appears to be a lucrative and emerging market (32). The NFT boom was significantly contributed to by a self-reinforcing loop of sales generating hype and hype fueling sales.

However, this bubble was burst in April 2022. This period was characterized by a sudden and significant drop in NFT sales and prices, which mirrored the patterns typically observed in economic bubbles. Consequently, public and media interest in NFTs waned considerably, with a notable decline in search interest and social media engagement surrounding NFTs.

This downturn was a stark reminder of the speculative nature and volatility inherent in emerging markets, leading to a more cautious and measured approach to NFTs in broader public discourse (33)(34) (35).

Examining the level of search interest regarding NFTs and macroeconomic blockchain-related volatility can serve as a useful means of gauging the overall health of the ecosystem. In doing so, this approach can provide immediate insights into the sentiments of the general public, potential movements within the market, and the global landscape of these technologies. This methodology can be integrated with other metrics to provide a more holistic understanding of the intricate and rapidly evolving worlds of NFTs and cryptocurrency.

The analysis of search interest in Non-Fungible Tokens (NFTs) and blockchain-related terms is a fundamental instrument to comprehend weekly NFT transactions and cryptocurrency volatility, including that of Ethereum (ETH) and Bitcoin (BTC). Primarily, search interest functions as a surrogate for market sentiment and public awareness. When there is an increase in search volume for these terms, it often points to a greater number of individuals showing an interest in these digital assets, which is highly probable to lead to increased demand. A decrease in search volume means reduced interest in the topic (36).

3

Research Methodology

3.1 Systematic literature review

For the purpose of this study, a combination of Systematic Literature Review process (SLR) and Systematic Mapping Studies are used. Systematic literature review (SLR) aims to provide an overview of a specific research area (37). The Systematic literature review approach has been used to summarize existing information and identify gaps in current research. It also serves as a venue for future investigation. Systematic Mapping Study, on the other hand, categorizes and structures the various types of study reports and outcomes that have been published. A variant of this is used to organize the material discovered and fit it to the demands of the research (38).

3.1.1 Definition of Research Questions

The creation of research question is initial step of the investigation and is pivotal to the study. The goal of this research is to study the NFT market dynamics and identify the key factors impacting NFT sales.

3.1.2 Conducting the search

The present literature study utilized the manual search method. To identify relevant literature for this study, the following sequential steps were executed :

- **Database Identification** : Quality research papers were obtained by searching online databases such as ACM, IEEE Explore, ArxIV, Google Scholar, etc.
- **Keywords and search phrases** : The present study utilized an overarching concept of "NFT" and "trends" in order to compile a comprehensive list of relevant keywords and phrases. Keywords, including "NFT", "Hype", "Ethereum", "Blockchain", "Transactions", "Sales", "Revenue", "Cryptocurrency", and "Anomalies", were subsequently employed in various databases to identify papers associated with the subject at hand. To achieve more detailed and specific results, specific variations and synonyms of the aforementioned keywords were utilized in conjunction with related

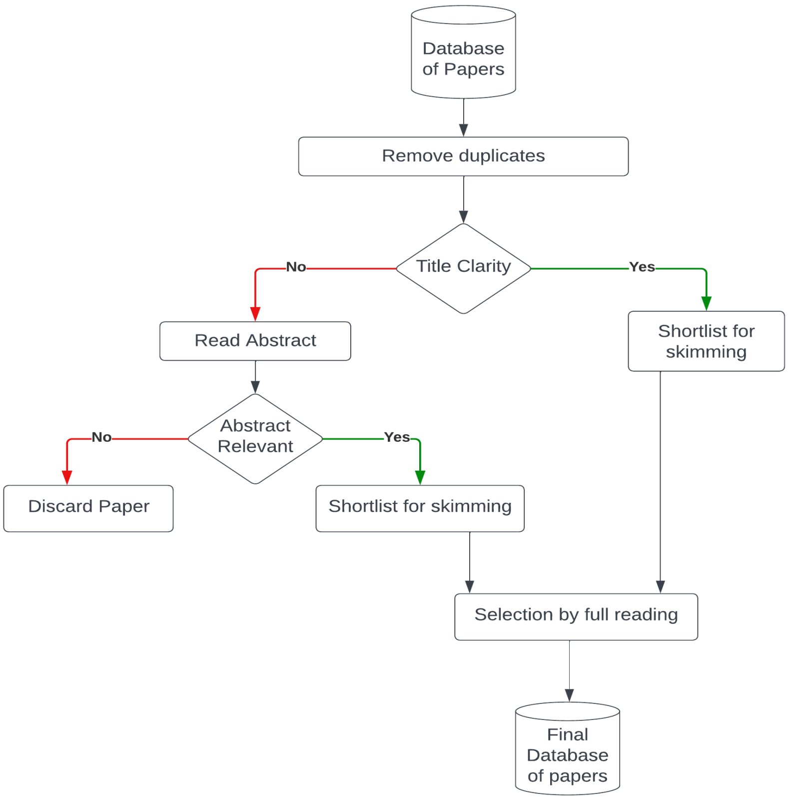

Figure 3.1: Paper selection process

phrases and combinations such as "Volatility in NFT markets", "Blockchain and NFT", "NFT search interest", "nft anomalies", "NFT and Cryptocurrency".

- **Citation chaining** : Having identified a relevant research paper, a thorough exploration of the references and citations was carried out. With reference to the citations, additional research publications were discovered from the bibliography.

- The results of the original search were analyzed and modified. Setting publication dates and focusing on certain journals and conferences aided in refining the scope of this study, which further facilitated in the identification of the most relevant academic works.

After a preliminary paper screening, a shortlisting process was enacted to allow for additional evaluations. The specifics of this selection procedure are visually represented in Figure 3.1. Subsequently, measures were taken to prevent the inclusion of duplicate papers that may have been published on multiple platforms. The remaining papers were then evaluated based on their titles to determine their relevance and subsequently shortlisted for further scrutiny. A detailed analysis of the abstracts of the papers was conducted to establish their relevance to the subject matter at hand. Any papers with irrelevant abstracts were not considered, resulting in a final selection of papers for in-depth analysis. These selected papers formed the foundation of our literature review. To facilitate the study, papers were categorized based on their respective topics, keywords, and sub-research questions defined by this study. To answer these questions, there was an emphasis on the domain problem, methodology, and takeaways from the literature.

3.2 Information about Papers

A total of 83 papers were considered for the study out of which, a few were eliminated based on the titles alone. From the remaining pool, abstracts of the papers were read. The relevant papers were then selected for a full reading. The final paper pool consisted of 31 papers. Figure 3.2 shows the distribution of papers based on the years.

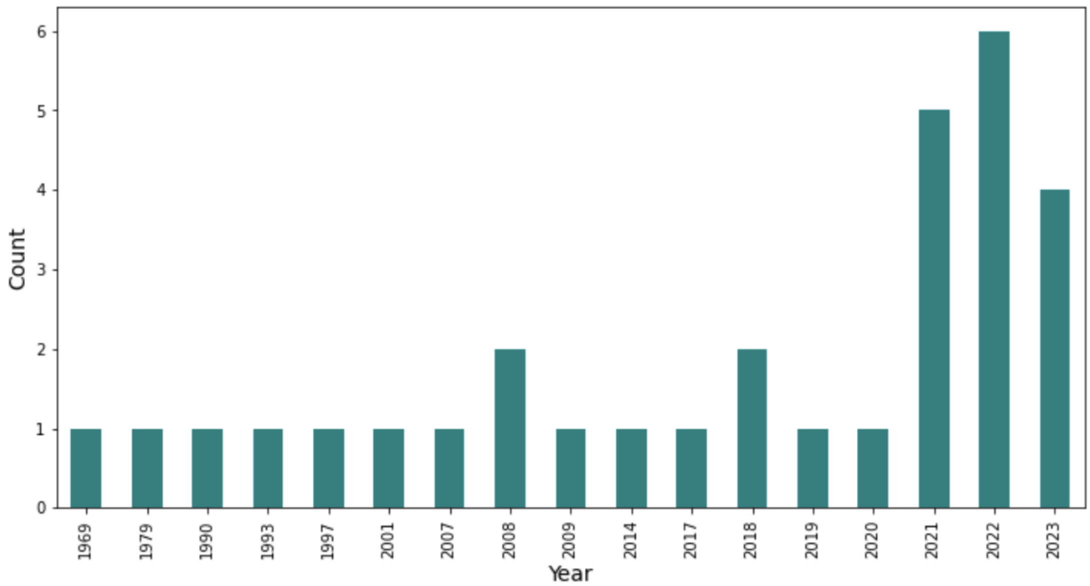

Figure 3.2: Distribution of Papers across years

The majority of publications appear to be from 2022. NFT first gained traction in 2017. Because it was still a novel topic, little research was conducted in the years that followed. In 2021 and 2022, the research focused on the NFT market. Prior to 2017, the majority of the papers were technical in nature, such as Bitcoin and Ethereum white papers.

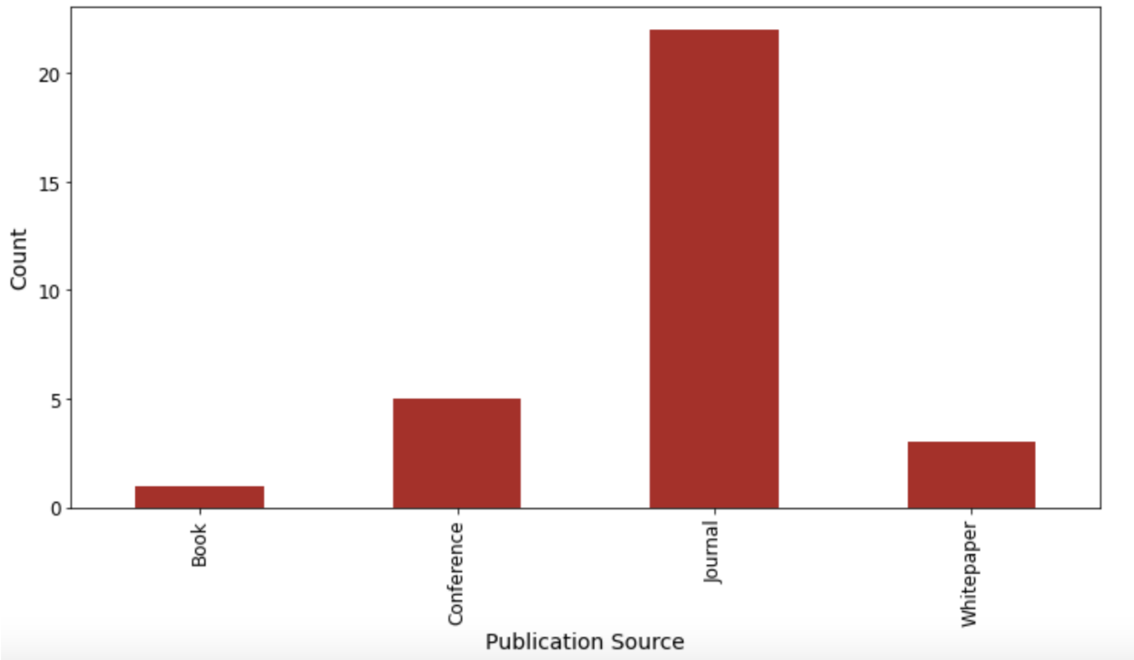

Figure 3.3: Literature Sources

The presented literature are extracted from diverse sources, encompassing a wide range of disciplines and platforms. The mentioned journals and conferences traverse numerous domains, ranging from computer science and technology, as showcased in publications like 'NeurIPS' and 'ACM Conference,' to economics and finance journals such as 'Economics of Innovation and New Technology' and 'Finance Research Letters.' Additionally, there is a notable presence of statistics and data science journals like 'Journal of the American Statistical Association' and 'Information Processing & Management.' Furthermore, specialized areas of research are also addressed, as evidenced by 'Nature Scientific Reports,' which is multidisciplinary but science-focused. The list includes both peer-reviewed journals like 'Econometrica' as well as pre-print archives such as 'arXiv', offering a mix of content. There is also an inclusion of the 'International Monetary Fund' which typically publishes globally-relevant economic research. A distribution of publication sources is highlighted in Figure 3.3.

3.3 Related Work

The research on NFT market space is still very nascent. NFT started gaining traction in 2017. The following section highlights relevant literature associated with the research. This is carried out to obtain crucial insights about prior work in the subject matter in order to more effectively answer to the research question(s).

3.3.1 Overview of the NFT Market

The Moonstream team examined 7 Million NFT transactions on the Ethereum blockchain (39) between April 2021 to September 2021. The study centered on the recent upsurge in NFTs and utilized statistical methods to classify NFTs as well as their consumers. The usefulness of NFTs was also scrutinized, while the report delved into the hype that surrounds them - analyzing both the natural market situation and to what extent it might be artificially created. White et al. (40) examine sales data from the OpenSea marketplace between January 2019 and December 2021. The market's economic activity and user behavior are both investigated. Due to the lack of transaction categorization through the API, the authors manually labeled transactions and noted the all-time high and subsequent fall in December. These findings were supported by the seller figures presented. The NFT market has seen a shift from games to art and collectibles, capitalizing on the fervor surrounding such items. Price volatility was also observed within this market. However, the authors did not provide a comparison between OpenSea and the overall NFT market.

Wang et al. (41) investigate the various strata of the NFT market. It is one of the preliminary comprehensive research of NFT systems. The research covers topics such as NFT abstractions, security evaluations, and future issues. The security assessments reveal flaws in the ecosystem that allow scams and fraud to flourish. The legal consequences, market laws, and general usability are also emphasized. The potential risks and challenges on investing are highlighted. Nadini et al. (42) conduct an analysis of a dataset comprising 6.1 million NFT trades. The findings indicate that the NFT market has a noteworthy transaction volume. The study focused on the market's progression over time, focusing on six major NFT categories,including art, gaming, and collectibles. Additionally, they provided a historical overview of NFT trades; the examination of NFT transaction history enabled them to gain insights into the market's prior performance. The study revealed a strong correlation between the prices of NFTs sold within the same collection.

3.3.2 NFT Sentiment Analysis

Examining the substantive content of a tweet, as well as public sentiment, can be instrumental in comprehending NFT trends through the lens of social media. Qian et al (43) employed EmoLex (an NRC Emotion lexicon) annotated words within tweets to identify eight emotions (Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, and Trust) and two sentiments (positive and negative). During the first quarter of 2022, there was a 50% decrease in sales Twitter activity related to NFTs, mainly due to the growing emphasis on the Ukraine war. This phenomenon could be ascribed to the over saturation of NFTs in the media. Moreover, the rise and fall of tweets corresponded to different days of the week. For example, Tuesday, Wednesday, and Thursday exhibited increased activity. By utilizing emotion analysis, it is plausible to infer that influential Twitter users can wield significant influence over the public.

Sawhney et al (44) model temporal irregularities in tweets and engagements using bidirectional encoder representations from BERTweet. An LSTM is beneficial since there is a temporal component. The influence on valuation is reduced when the time gap between tweets is substantial. The greater the reach of the tweet, the greater the impact on sentiment polarity. The historical context is critical in determining the influence. An ideal time gap is required, as tweets with a shorter time gap are difficult to evaluate and older tweets lead to noise in the model. As a result, tweets' short-term reliance on NFT valuation reflects the market's dynamic and fast paced nature. Positive tweets with higher reach increased, whereas negative tweets with lower reach decreased. Price variations are driven by the intensity and polarity of public sentiment, which is then influenced by important individuals.

Luo et al. (45) study the predictability of NFT price moves through tweets-extracted word features. The authors use a Granger causality test to investigate the causal relationship between the number of tweets and the NFT average prices. They also use prediction tasks (SVM,MLP and Transformers) to analyze the feature importance of tweets-extracted word features in predicting NFT price moves. The Granger causality test indicates that the number of tweets has a positive impact on the price for most of the top authentic projects, while market-related and NFT event-related words contribute positively to predicting price moves, and the sentiment analysis of NFT project tweets reveals a generally positive sentiment.

Ante et al (46) use event study approach to analyse Musk's twitter activity on short term crypto returns and volume. Studying 46 Twitter events, the study revealed significant increases in trading volumes. There was a 3.58% return within two minutes after a tweet and 4.79% return within an hour after the tweet. The return effects were specific to Dogecoin and not Bitcoin. This study provided the stakeholders with an idea about the impact of specific tweets and have an informed opinion about investments. However, the study does not consider other factors that may affect cryptocurrency markets, such as regulatory changes or macroeconomic events.The events analyzed in the study may consist of several consecutive tweets, and the analysis does not account for compound effects.

3.3.3 Time Series Analysis

Multiple time series analyses like Vector Autoregressive Model (VAR) and Wavelet coherence technique are used to investigate the impact of Bitcoin and Ether returns on the next week's NFT popularity (as measured by Google searches) (47). These help to understand how different components of the time series (short-term volatility vs. long-term trends) are related. It is found (using VAR) that the previous week's Bitcoin returns increase attention towards NFTs. Wavelet coherence technique suggests that investors are more attracted to NFTs after a spike in both Bitcoin and Ether returns.

Dowling et al (48)investigate whether NFT pricing is related to crypto pricing. They chose Bitcoin as the largest crypto market and Ether as the primary currency for trading NFTs. The NFT data represents secondary market exchanges in CryptoPunk images, Axie Infinity game characters, and Decentraland LAND tokens, all of which are examples of their respective collectible categories. Using the volatility spillover methodology, the volatility shocks to and from the NFT markets, as well as between the markets, are calculated. Wavelet coherence analysis (in time and frequency) is used to investigate market co-movement. The direction of spillover is determined by an extension of phase position in wavelet analysis.

Another intriguing consideration is the amount of active NFT wallets. The consequences for NFT sales are that the number of active NFT wallets is favorably related to them. Ante et al (49) employed a Vector Error Correction Model (VECM) and Granger Causality to examine the relationship between the cryptocurrency and NFT markets. The study finds fascinating trends, such as the effect of Bitcoin price shocks on NFT sales and the effect of Ether price shocks on the number of active NFT wallets. These findings offer insight on the volatile nature of cryptocurrency markets and their implications for the NFT ecosystem.

A Bitcoin price shock causes an increase in NFT sales. A drop in Ether, on the other hand, reduces the number of NFT wallets. NFT has no influence on crypto pricing. A dip in crypto affects NFT purchase power, hurting the market as a whole.

3.3.4 Anomaly Detection

Xin et al.(50) provide a framework for anomaly detection in cloud applications using an ensemble based method. They also compare the performance of the proposed AI-based deep ensemble method with other methods in terms of detection accuracy, robustness, and prediction ability.

Pelechrinis et al.(51) propose a methodology to identify anomalous peer-to-peer transaction of the NBA TopShot, an NFT marketplace. The method includes building a model to predict the profit from selling a specific collectible and then using RFCDE (random forest model for conditional density) to model the errors from the profit models. Transactions with a probability of being anomalous less than 1% are labeled as such. The authors then analyze the trade networks formed from these anomalous transactions and compare it with the full trade network of the platform to evaluate the model's classification of transactions. Through analyzing trade networks formed from anomalous transactions and comparing them to the full trade network of the platform, it was found that these two networks are statistically different in terms of network metrics such as edge density, closure, node centrality, and node degree distribution. This network analysis provides additional evidence that these transactions do not follow the same patterns as the rest of the trades on the platform, but further auditing is required to determine their legality.

3.3.5 Research Gap Analysis

While prior research has focused on social media sentiment, general market overviews, and the relationship between cryptocurrency and NFTs, there seems to be little information on the daily operations of NFT marketplaces. Some literature focus on analysing nature of tweets by extracting keywords. This study groups keywords used for google searches into different sentiments like positive, negative and neutral. There has been work on anomaly detection, but univariate time series data is not studied. This research aims to bridge this gap by provide a comprehensive analysis of the daily workings of the NFT market. The analysis includes studying the interplay between sales, search interest, and crypto volatility. Anomalous sales are identified, and finding factors impacting them is crucial for identifying potential issues or opportunities in the NFT space.

4

Methodology

Navigating the dynamic nature of the Non-Fungible Token (NFT) market necessitates a methodical and systematic approach. The methodology relies on rigorous data-driven techniques which scrutinize the various facets of the market. The initial stages involve data preprocessing and feature engineering, which form the fundamental basis for constructing and refining regression models. Feature selection further enhances the analysis by highlighting relevant predictors. In addition to these quantitative measures, this study utilizes behavioral metrics to examine the interplay between search interest of NFTs and the volatility of the wider cryptocurrency market. Furthermore, any anomalies in NFT sales, which may indicate abnormal market behavior or emerging trends, are identified and subjected to detailed investigation. This comprehensive methodological framework guarantees a holistic perspective of the evolving NFT marketplace. Methodology followed for this study is illustrated in Figure 4.1.

4.1 Factors impacting NFT Sales

Understanding the factors impacting NFT sales is critical as it helps understand the current market health. Additionally, with the NFT space rapidly evolving, such insights are crucial for adapting to shifts and capitalizing on emerging opportunities.

4.1.1 Feature Engineering

Feature engineering is the process of selecting, transforming, creating, or modifying features from raw data (52). By creating new features from existing ones, hidden patterns in the data that might not be immediately apparent can be unveiled. To capture temporal patterns, lagged features, percentage changes, volatility based features are created.

4.1.2 Feature Importance

Now that the features are engineered in section 4.1.1, it is imperative to find the importance of features on daily sales. Feature importance techniques elucidate which variables predominantly steer sales. By identifying and quantifying the importance of such features,

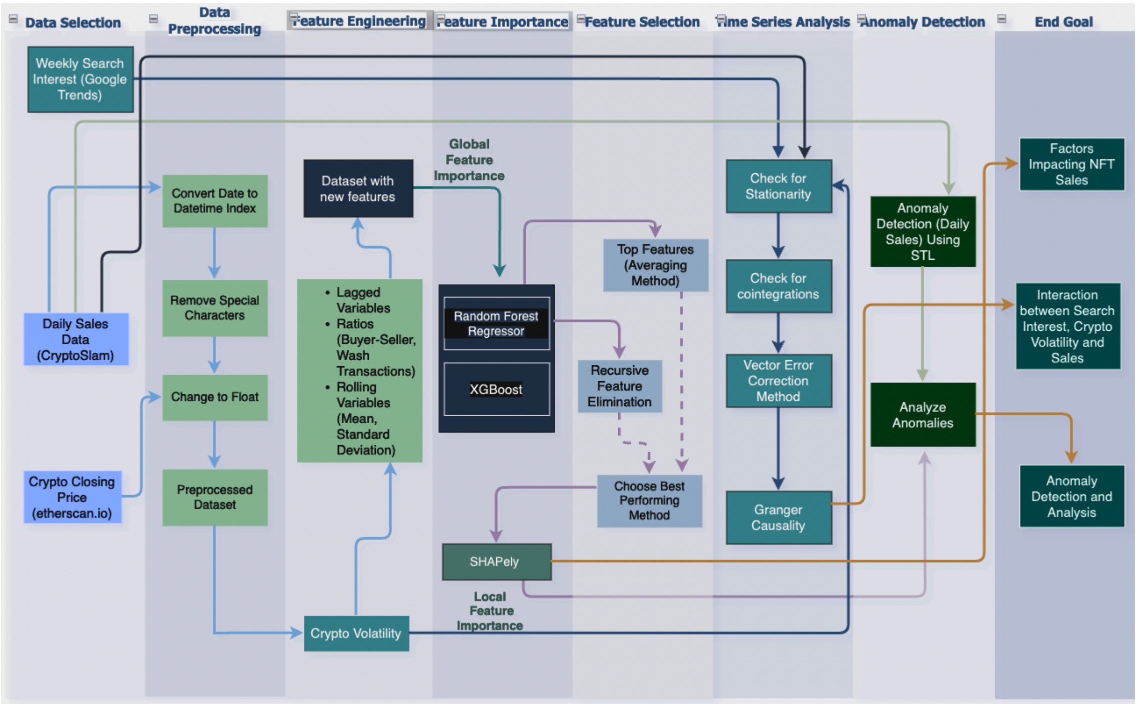

Figure 4.1: Methodology Diagram

stakeholders can optimize investment and anticipate future sales with greater precision. The goal is to find the most important features impacting daily NFT sales, making this a regression task. Daily NFT sales is a continuous variable, hence classification is not very useful. This project makes use of two powerful ensemble methods - Random Forest and XGBoost to compute feature importances. Ensemble learning method is a technique that combines predictions from multiple machine learning algorithms develop a prediction that is more accurate than a single model.

4.1.2.1 Random Forest

Random forest regression is a supervised machine learning algorithm which uses an ensemble learning method. A Random Forest is a bagging technique which constructs multiple decision trees during training time and the prediction is the mean of the features across all the trees. A random forest is a collection of tree predictors $\{h(x, \Theta_k) : k = 1, 2, 3, \ldots\}$, where Θ_k is the observed input vector of length k.

It is important to retain the temporal order of the data while splitting data into training and testing. It could otherwise lead to data leakage, where the model has access to future information during the training phase. This could further lead to severely optimistic performance estimates, making the model unreliable for unseen data. In this case, a simple train-test split is performed in a chronological order.

During the training phase, the Random Forest model uses input features from training data to help generate predictions. Typically, the forest comprises of individual trees, each constructed using a bootstrapped sample, which entails a random selection with replacement from the training data. When each tree grows, a random subset of features is selected at each node and the optimal split among these features is determined to partition the data. The recursive repetition of this process yield the growth of the tree to a predetermined depth. This process ensures that each tree in the forest is unique due to the forest's "random" nature and random selection of features for each split. To make predictions on the test data, features are passed to each tree in the forest, resulting in one prediction per tree. The final prediction of a Random Forest regressor is the average of predictions of all individual trees in the forest. This method mitigates high variances of predictions and results is a stable and accurate model.

In this case, the model is trained on past data and is used to make prediction on future (unseen) data. The features created include lagged variables (past observations), rolling statistics (moving averages, moving standard deviations), volatility and other independent variables.

For a new data point x, each of the n_t trees in the ensemble makes a prediction $y_i(x)$. The final prediction of the random forest regressor is the average of these individual predictions:

$$\hat{y}(x) = \frac{1}{n_t} \sum_{i=1}^{n_t} y_i(x) \tag{4.1}$$

4.1.2.2 XGBoost

XGBoost (eXtreme Gradient Boosting) is an efficient and scalable implementation of gradient boosted tree algorithm. Gradient boosting is a supervised learning algorithm which aims to predict a target variable combining predictions from weaker models.

XGBoost uses a collection of K 'regression trees' to learn a model from labelled data. Regression trees appear to be very similar to regular decision trees, except that the leaves are associated with learned real number outputs rather than class labels. Each tree has T leaves, each associated with a learned output value $\{w_i\}_{i=1}^{T}$ (53). The final predicted value is a simple sum of the outputs of the individual trees:

$$\hat{y} = \sum_{j=1}^{K} f_j(x) \tag{4.2}$$

for sample input $x \in D \subset \mathbb{R}^m$. Each tree is defined by an index function $q(x) : D \to \{1, 2, ..., T\}$ that maps any input sample x to a leaf of the tree and thus the output value $w_{q(x)}$.

The loss function for training is given by

$$L = \sum_{k=1}^{N} l(\hat{y}_i, y_i) + \sum_{k=1}^{K} (\gamma T_k + \frac{1}{2}\lambda \|w_k\|), \tag{4.3}$$

where l is a 'differentiable convex' loss function, T_k is the number of leaves in the kth tree, w_k are the output weights of the kth tree, and λ, γ are hyper-parameters. XGBoost works as an optimization algorithm which aims to minimize a loss function by identifying the set of predictions (derived from the model). The loss function l, measures the degree of deviation between model predictions and the actual target values.Note that the last two terms are for regularization. The first regularization term appears intended to prevent the trees from getting to deep and large, which would help prevent overfitting and control training and evaluation costs. The other term is intended to prevent the learned parameter values from getting too large in magnitude.

As mentioned in the previous subsection, the temporal order has to be retained why splitting data into training and testing.

4.1.3 Feature Selection

After creating new features, it is important to select the best features for predictions. It is plausible that certain attributes may not be useful in forecasting and, in fact, could potentially have a detrimental effect on the model's performance.

4.1.3.1 Recursive Feature Elimination

Recursive Feature Elimination (RFE) is a feature selection method used to refine the feature set using all created features. RFE is a feature selection method that fits a model and removes the weakest features based on feature importance, till the target number of features is reached. At each step, the selected model is trained on the remaining features, and the least important ones are eliminated. This process is recursively repeated until a desired number of features is achieved.

4.2 Feature Importance for Different Time Periods

To find feature importance across different time windows, local feature importance is calculated using SHAPely explainer values. Local feature importance refers to the individual contribution of each feature to a particular prediction. Global feature importance outlines the general significance of a feature across all instances. The aim of local feature importance is to explain why a certain prediction was made for a particular data point.

4.2.0.1 SHAPely

Figure 4.2: SHAP Global Importance

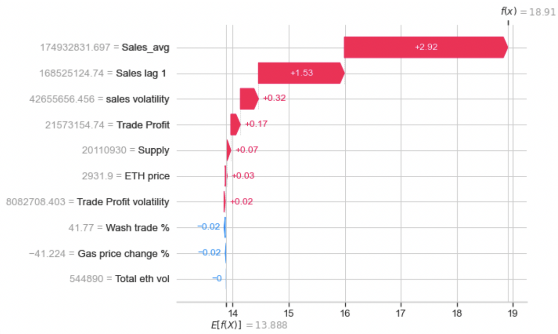

Figure 4.3: SHAP Local Importance

While the above methods (Random Forest and XGBoost) yield high accuracy, they are not explainable. To address this issue, a unified approach called SHAP (SHapley Additive exPlanations) is used. For a given feature and an input data point, SHAP assigns a feature importance value, thus aiding model explanability. The importance of ith feature ϕ_i is given by (54)

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{F!} [f_{S\cup\{i\}}(x_{S\cup\{i\}}) - f_S(x_S)] \tag{4.4}$$

where F is the set of all features, and, for a given subset S of features, f_S is the model trained on the subset of features, and x_S is the set of values of the features S in data point x. SHAP values for global and local feature importance (for a specific data point) are plotted in Figures 4.2 and 4.3 respectively. Note that models f are obtained from fitting the data on a Random Forest regressor.

4.3 Search Interest and Volatility

As explained in an earlier chapter 2.5, it is important to take search interest into account to understand market dynamics. Evaluating these intricate bonds between NFT market, crypto volatility and search interest could potentially be helpful in recognizing the underlying elements that cause shifts in cryptocurrency volatility, search interest, and weekly sales, and can be employed to design approaches for better managing these connections and minimizing risks.

4.3.1 Augmented Dickey-Fuller test

The Augmented Dickey-Fuller (ADF) test is a statistical test used to determine if a time series is stationary or has a unit root (55). A non-stationary time series could be converted to a stationary sequence by differencing the data. The ADF test is considered "augmented" due to the incorporation of lagged terms of the dependent variable to account for autocorrelations in residuals. The null hypothesis of the ADF test is that the series has a unit root (i.e., it is non-stationary). A series is stationary if the test statistic is below the defined threshold (generally p-value < 0.05). Stationarity is property of a time series wherein the statistical characteristics (mean and variance) do not change over time. It is imperative to ensure stationarity as the majority of time series models require this attribute, and their soundness hinges on it. If a sequence is non-stationary, the predictions made by the model may lead to erroneous conclusions.

4.3.2 VECM

Vector Autoregression (VAR) and Vector Error Correction Model (VECM) are two widely used multivariate time series models. Despite sharing some similarities, they are used differently based on the characteristics of the time series data. VAR is a type of autoregressive model that models each variable as a function of its past values, with the predictors being lags of the series. It is particularly suited for stationary data, which can be obtained by differencing the original time series. Mathematically, a VAR(p) of order p is expressed as a system of p equations, where each equation is a linear combination of the p lags of all variables.

Let Y_t be the k-dimensional vector of values at time t of k time series, α is the intercept, β_1, $\beta_2 \ldots, \beta_p$ are coefficient $k \times k$ matrices of lags of Y up to order p, ϵ_t is the error term.

Then,

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \epsilon_t. \tag{4.5}$$

The matrix coefficients (cross-)correlate the different time series in the data Y.

VAR models have limitations, such as their sensitivity to the choice of lag order and the requirement of the stationarity assumption. A Vector Error Correction Model (VECM) is used when the time series is non-stationary and cointegrations are present. The identification of cointegrations is carried out using the Johansen Cointegration test 4.3.3. As a result, assuming $0 < r < p$, where r denotes the number of cointegrating relationships and p is the total number of variables, the VECM model is the most fitting.

4.3.3 Johansen Cointegration Test

Time series data, specifically financial data, often exhibits non-stationarity. However, it is possible that an individual time series is non-stationary, while the linear combination remains stationary, which is known as cointegration. Such data is particularly useful in obtaining consistent outcomes through techniques that take into consideration the co-integration. Johansen cointegration test is a statistical method utilized to determine the number and presence of co-integrating vectors (56). It is tailored for multiple time series, typically exceeding two.

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-i} + \mu + \varepsilon_t \tag{4.6}$$

Π is the matrix capturing the long-run relationships (cointegration). The rank of Π gives the number of cointegrating vectors.

4.3.4 Granger Causality

Granger causality is a statistical technique that attempts to determine if one time series can more accurately predict another time series based on the information included in its own past. It should be noted that the term "causality" in this context is a misnomer. It does not connote genuine causation in the sense of cause-and-effect, but rather a predictive capacity (57).

VECM for Granger causality tests in the presence of cointegration accounts for both the short-term dynamics and the long-term relationship, making the causality test more comprehensive and meaningful. Short-term causality tests if the lagged differences of series

X helps predict the current difference of series Y. This is similar to the Granger causality test for stationary series. Long-term Causality (via Error Correction Term) tests if the error correction term helps predict the change in series Y. The p-value less than assigned threshold (0.05) indicates that lagged X Granger-causes Y.

4.4 Anomaly Detection

Anomaly constitutes an observation or a sequence of observations that deviates from the overall distribution of data. Typically, such anomalies comprise a minor fraction of the given dataset. There exist three distinct types of anomalies, namely: point, collective, and contextual. In this particular endeavor, we concentrate on contextual anomalies, commonly referred to as "conditional outliers," which represent anomalies that are specific to a given context and would not qualify as outliers if analyzed independent of said context. The aberration found in the chronological sequence data is a point (outlier) that differs from a regular pattern (58).

4.4.1 Seasonal-Trend Decomposition

Seasonal-Trend decomposition using LOESS (STL) is a method that decomposes a seasonal time-series into seasonal, trend, and residual components (59).

$$Y_v = T_v + S_v + R_v \tag{4.7}$$

where Y_v is the univariate time series which is decomposed into Trend (T_v), Seasonality (S_v) and Residuals (R_v).

Since a time series data is in use, this method is particularly helpful in identifying sudden spikes and dips. In the specific context of the time series data - *Sales (USD)* is treated as univariate data. the application of STL decomposition allows for a more profound comprehension of the underlying patterns and behaviors that are unique to each metric. For example, the Sales (USD) column may demonstrate a noticeable trend that indicates an overall growth or decline of sales over time. The 'noise' or irregular movements that cannot be attributed to the trend or seasonality is captured by the residuals. Figure 5.7 captures the decomposed Sales data into trend, seasonality and residuals. By understanding these components separately, it becomes easier to isolate effects and develop strategies or forecasts based on individual time series dynamics. The residual, in this case, will highlight any anomalies or unexpected events that may affect these metrics. By decomposing this time series separately, stakeholders would be able to strategize based on this metric's individual characteristics, despite its origin in a multivariate time series data set.

After decomposing the time series for seasonality, trends and residuals (section 4.4.1), a normality test is done on residuals. Residuals are the component of a time series are not explained trends or seasonality. Scale estimators like standard deviation and median absolute deviation (MAD) are used to study the variability of data. This aids in identifying anomalies. The application of standard deviation is ruled out due to the data not being normally distributed. The median absolute deviation (MAD) is an alternative robust scale estimator. The downside of MAD is that it assumes symmetry in data. Plotting the STL decomposition, it is observed that there is no particular symmetry. A good alternative to MAD is the S_n estimator of scale proposed by Rousseeuw and Croux (60).

$$S_n = c \times \text{Median}_i \left\{ \text{Median}_j \left| x_i - x_j \right| \right\} \tag{4.8}$$

For each data point in the residuals x_i, the median of absolute differences between x_i and every other data point x_j is calculated. The median of these medians is them multiplied by a scaling constant c to give the S_n estimator.

The robust S_n estimator has the ability to provide reliable estimates across different distributions. The constant 1.1926, while derived from the normal distribution, serves as a general-purpose scaling factor for different distributions. Using this constant ensures that the scaled S_n remains a meaningful measure of dispersion, retaining its properties of being resistant to outliers and providing a stable measure of spread.

If $\tilde{x}$ is the median of the dataset X, the upper and lower threshold (τ_u and τ_l) for anomaly detection are taken as

$$\tau_u = \tilde{x} + 6 \times S_n \tag{4.9}$$

$$\tau_l = \tilde{x} - 6 \times S_n \tag{4.10}$$

Subsequently, positive and negative anomalies are identified by comparing residual values with thresholds defined above. Note that positive anomalies refer to spikes in sales and negative anomalies are sales which have dipped.

```
positive_sales_anomalies = data[residuals > upper_threshold]
negative_sales_anomalies = data[residuals < lower_threshold]
```

4.5 Evaluation Metrics

For a regression model f with n observations, following are the commonly used evaluation metrics:

- Root Mean Squared Error (RMSE)

$$\text{RMSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - f(\mathbf{x}_i))^2 \tag{4.11}$$

  The Root Mean Square Error (RMSE) computes the average of the squared errors, which results in a greater sensitivity to outliers. Moreover, RMSE preserves the same scale as the original dataset, hence its interpretation can be subjective.

- R^2 : (model.score) is intuitive measurement of how well the predictions fit the observed values. This scores is computed for both test and train data. The values range between 0 and 1 (or negative if the model is worse than a naive baseline)

$$R^2 = 1 - \frac{\sum_i^n (y_i - f(\mathbf{x}_i))^2}{\sum_i^n (y_i - \bar{y})^2} \tag{4.12}$$

  given a test set with true values y_i of the output variable corresponding to feature values $\mathbf{x}_i$. $\bar{y}$ is the mean value of the output variable over the test data set.

- Mean Absolute Percentage Error (MAPE) is the percentage equivalent of mean absolute error (MAE). Mean absolute percentage error measures the average magnitude of error produced by a model, i.e, how far off predictions are from actual values. Since MAPE is a percentage error, is is scale-independent.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_i - f(\mathbf{x}_i)}{y_i}\right| \tag{4.13}$$

  The value is then multiplied by 100 to give the metric in percentage terms.

5

Experimental Setup and Results

This chapter discusses the data used, experiment design and results.

5.1 Factors impacting NFT Sales

The experimental setup for finding factors impacting daily NFT sales involves several elements like data selection, preprocessing, feature engineering and selection, feature importance and finally evaluation metrics.

5.1.1 Data Selection

The daily sales of Non-Fungible Tokens (NFTs) from January 1, 2019 to April 30, 2023 are sourced from the CryptoSlam website (61). The dataset is made up of different columns that relate to various parameters like 'Date', daily NFT sales volume, average sales, and the number of buyers and sellers. The data is also inclusive of macroeconomic factors like the daily closing price of Bitcoin (BTC), Ether (ETH), and the daily gas price (Gwei). This data was obtained in a CSV format from etherscan.io (62). Daily closing prices of Bitcoin and Ether provide a consistent reference point, reflecting market consensus at day's end, while averages can be skewed by short-term volatility, potentially misrepresenting the crypto's influence on NFT sales. This comprehensive dataset offers a multilayered perspective of the blockchain space, encompassing the NFT and cryptocurrency market. Analysis of this dataset could reveal insights which could hold significant values for stakeholders interested in the market.

5.1.2 Data Collection

This section elaborates on how aforementioned data was obtained from Cryptoslam and Etherscan (62). Selenium is a python package used to to scrape dynamic web.The Cryptoslam web page's source HTML was obtained and further processed based on different classes of tags. The Selenium API uses the WebDriver protocol to control web browsers like Chrome, Microsoft Edge and Safari. For our use case, we have made use of the

ChromeDriver binary in the `headless` mode. This opens a Chrome window which is controlled by Selenium. The source HTML is then parsed to obtain relevant data. Using Chrome's `inspect element` feature, is it easy to locate and inspect any element in question. In addition to this, the WebDriver's `find_elements` method searches for all elements based on the tag name. Tags which are relevant to methods corresponding to data columns above are extracted for further analysis. Etherscan (62) consists of data related to Bitcoin, Ether and Gas prices, which could be downloaded in CSV format.

5.1.3 Data Properties

The `Date` column represents the day of each record in a YYYY-MM-DD format. It ranges from 2019-01-01 to 2023-04-30, providing a comprehensive view of the market changes across these years. The `Daily NFT Sales` column represents the total volume of NFT sales that occurred each day. This includes data from various NFT platforms and is the total value in a common currency USD. `Bitcoin Price` and `Ether Price` columns represent the daily closing price of Bitcoin and Ether, respectively, in US Dollars. The `Gas Price` parameter, measured in Gwei (a unit of Ether), represents the average gas price for Ethereum transactions each day. Gas prices fluctuate based on network congestion and transaction complexity, which can significantly impact the cost and speed of buying or selling NFTs on Ethereum-based platforms. Finally, `Supply` refers to the total number of NFTs traded in a particular day.

The dataset used in this investigation consists of data between 2019 and 2023. It comprises 1581 rows presented in a time series format. Unlike traditional stock markets, which operate on fixed opening and closing times, cryptocurrency markets remain open around the clock. This characteristic of cryptocurrency trading, especially Bitcoin and Ethereum, stems from their decentralized nature, which facilitates continuous trading and ensures the consistent availability of price data. Results of exploratory analysis of our dataset are presented in section 5.1.5.

5.1.4 Data Preprocessing

Data preprocessing is a vital step in any data driven project. It involves preparing and cleaning the data to ensure that it's in the best format for analysis. The process of data preprocessing often includes removing or correcting inconsistencies, converting data types, dealing with missing values, and potentially transforming or normalizing the data. In this particular case, we are dealing with a dataset related to Non-Fungible Token (NFT) sales.

A straightforward data cleaning procedure was applied to systematically eradicate special characters from the dataset using python's `replace`() method. Subsequently, the date format, originally in "Month Date, Year," was transformed into a more convenient `datetime` using pandas' `pd.to_datetime()`. This conversion facilitated the extraction of particular components of the date, such as day, month, and year, and their reassembling into a more manageable format. Following this, the Bitcoin and Ethereum volume columns in the dataset were initially expressed as strings like "100M" and "100K." While this format is user-friendly for readability, it is not optimized for computational tasks. Therefore, these columns were transformed into their respective numerical. Finally, the Sales columns in the dataset were also expressed as strings. All the remaining columns were converted to `float` for uniformity.

All of the aforementioned steps are essential constituents of the data preprocessing procedure. The data preprocessing mechanism guarantees that the dataset is devoid of any irregularities or inaccuracies that may influence subsequent analysis or prediction. The cleaner and more standardized the data is, the better the results of any data driven algorithm will be.

5.1.5 Exploratory data analysis

We begin with a statistical summary of the data.

Attribute	Min Value	Average	Max Value
NFT Sales	$4,049	$33.79M	$578M
Bitcoin Closing Price	$3397.70	$23,575.42	$67,927
Ethereum Closing Price	$104.55	$1339.46	$4808.38
Daily Bitcoin Volume	-	$13.90M	$752M
Daily Ethereum Volume	-	$8.6M	$991M
Trade Profit	-$106M	$1.22M	$78.02M
Gas Price (Gwei)	7.32	55.77	709.70
Supply	0	14.65M	28.54M
Unique Buyers	49	32,703.95	1,77,248
Unique Sellers	41	29,822.09	1,32,143

Table 5.1: Descriptive statistics of dataset

Table 5.1 displays important statistics for the dataset. The highlight is the 'NFT sales' variable, whose minimum value is $4,049 and it peaks at $578M. This is important to illustrate the highly skewed nature of data. Ethereum and Bitcoin closing price hit a maximum of $4,800 and $68K respectively. Trade profit goes as low as -$106M, which means a heavy loss was incurred that day. A maximum profit of $78 was made. The maximum number of NFT assets in supply was 28.5 million.

5.1.6 Correlation

Correlation is a statistical measure that expresses the degree to which two variables are linearly related. A correlation heatmap serves as a valuable tool for visually analysing the interrelationships among various variables. The correlations between the variables in the dataset are depicted in Figure 5.1. A divergent color scheme is used to accentuate the positive and negative correlations in a distinctive manner. To comprehend the factors that influence the `Sales (USD)`, its corresponding correlations are analyzed.

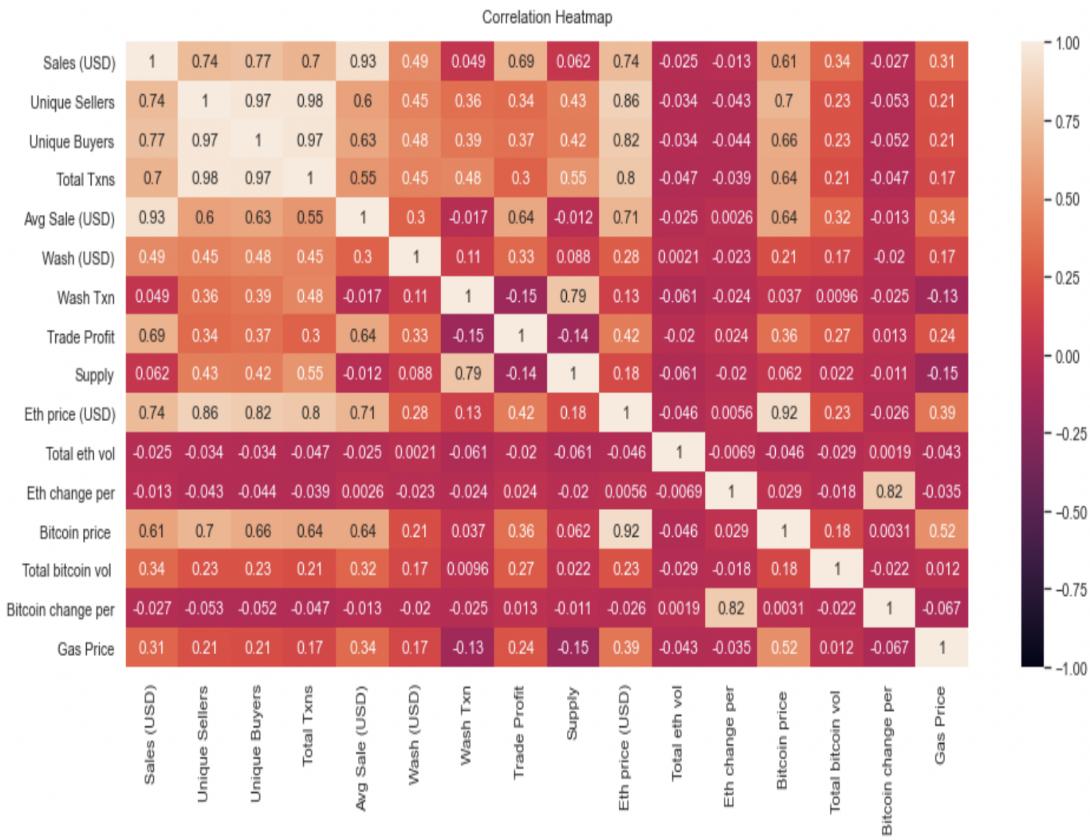

Figure 5.1: Correlation Heatmap

In a market, a favorable correlation between the quantity of distinctive sellers and buyers who have participated potentially suggests that with the rise in the number of market participants, the overall volume of transactions, and in turn, the total sales in USD, would also experience an increase. `Wash (USD)`, exhibits a positive correlation with `Sales (USD)` due to the possibility of artificially inflating trade sales numbers. The total number of transactions (`Total Txns`) naturally showcases a favorable positive correlation with `Sales (USD)`, as an increase in transaction count would very likely lead to an increase in total sales amount.

The correlation between `ETH price (USD)` and the target variable in question is stronger, indicating a heightened sensitivity to changes in `Sales (USD)` as opposed to changes in `Bitcoin Price`. On the other hand, the negative correlation between percentage changes in Bitcoin, Ether prices could be attributed to the significant price volatility, which could make market participants more cautious and reduce `Sales (USD)` as traders may avoid heavy transactions in highly volatile market conditions.

The correlations present within the datasets might not be a reliable way to determine the significance of some characteristics due to various factors. Primarily, it must be emphasized that strong associations among factors do not automatically imply causality. It is challenging to isolate the individual influence of each feature when datasets display multicollinearity as a result. Secondly, the given variables do not capture the temporal dependencies and trends inherent in time series data. These issues make raw correlation values unreliable predictors of sales. The process needs more features than what the natural dataset offers. Feature engineering process helps create powerful new features and modify existing ones to help uncover complex relationships, which the original data might have missed. In a volatile and dynamic domain like NFT and Cryptocurrency, external factors and previous states can have a profound impact on current observations.

5.1.7 Feature Engineering

Feature engineering is the process of selecting, transforming, creating, or modifying features from raw data to uncover hidden patterns. Historical data (lagged variables) were created using the `shift()` function from Pandas. The Wash Trade % is a feature that indicates market manipulation, while the ratio of Buyers to Sellers is crucial for understanding market dynamics. A higher Wash Trade % value may indicate potential market manipulation or artificial activity. Logarithmic returns are preferred over simple returns in financial analysis due to their time-additive nature, ease of calculations over multiple time periods, and account for compounding effects. Cryptocurrency volatility is calculated using the Pandas `rolling` function with a 7-day window. The calculation of volatility for cryptocurrency varies from conventional stocks due to its round-the-clock operation, greater price instability, and lesser regulation. `Sales average` and `Sales volatility` were computed using `shift(1).rolling(window=7)`, mean and standard deviation respectively. The current day sales data point is excluded as it might cause data leakage.

Feature engineering is the process of selecting, transforming, creating, or modifying features from raw data (52). By creating new features from existing ones, hidden patterns in the data that might not be immediately apparent can be unveiled.

Feature Type	**Features**	**Calculation**
Lagged Variables	Total eth vol lag 1,Total bitcoin vol lag 1,Wash transaction ratio lag 1,Wash trade % lag 1,Sales lag 1 ,Gas price lag 1,Trade Profit lag 1, Buyer Seller lag 1	$x_t \leftarrow x_{t-1}$
Percentage Change Variables	Gas price change %, Eth change %, BTC change%	$\left(\frac{x_t - x_{t-1}}{x_{t-1}}\right) \times 100$
Ratios	Buyer seller ratio	$\frac{Buyers}{Sellers}$
	Wash transaction ratio	$\frac{Washtransactions}{TotalTransactions}$

Table 5.2: Feature Engineering

Creating historical data (lagged variables) mitigate the effects of using same-day data. The lagged variables are created from current features by shifting the value upwards by 1 day. The current features are then dropped. `Wash Trade %` is the percentage of wash trade volume to total sales is feature that is indicative of market manipulation. Wash trading refers to the deceptive practice of buying and selling the same asset to create misleading, artificial activity in the marketplace. A high wash trade percentage might suggest that a significant portion of the trading volume is not genuine, which can mislead genuine traders and investors. The ratio of Buyers to Sellers is a critical aspect of understanding market dynamics. A ratio exceeding one denotes an increase in buyers, indicative of a bullish market sentiment. In contrast, a ratio lower than one may suggest bearishness (63). Monitoring this aspect over time can provide valuable insights into variations in market demand and supply equilibrium. `Wash Transaction Ratio` provides a direct measure of the proportion of wash transactions to total transactions. Like the Wash Trade %, a higher value of `Wash Transaction Ratio` might indicate potential market manipulation or artificial activity. It is essential for regulators and trading platforms to monitor this feature to ensure fair trading practices.

Intrinsic sales value like sales average, lagged sales and sales volatility are computed to find their effects on daily sales. Sales volatility is the standard deviation of sales computed over a 7-day window, excluding today's sales. Similarly, sales average is the sales mean over a 7-day window, also excluding current day sales.

5.1.7.1 Volatility

In finance, "returns" refer to the gain or loss of an investment over a specific period, usually expressed as a percentage. Logarithmic returns are preferred over simple returns in financial analysis because of their time-additive nature, and allow for easy calculations over multiple time periods. They treat price fluctuations with a symmetric approach, exhibit more of a normal distribution, and account for compounding effects. They also mitigate extremes in sharp price declines and provide mathematical simplicity in various financial models. Taken together, these attributes make logarithmic returns more suitable for sophisticated financial modeling and analysis. Returns are further used to calculate volatility. `Ethereum` and `Bitcoin` daily returns are calculated using the formula below :

$$\rho_i = \log \frac{p_i^c}{p_{i-1}^c}, \tag{5.1}$$

where ρ is the return and p^c are the closing prices.

The computation of volatility v for cryptocurrency varies from that of conventional stocks as a result of its round-the-clock operation, greater price instability, and lesser degree of regulation. Additionally, it is subject to substantial price fluctuations resulting from news, regulations, or large transactions, causing conventional volatility models to be less dependable.

$$v = \sigma(\rho_T)\sqrt{T}, \tag{5.2}$$

where v is the volatility, T is the number of trading days, ρ_T is the return over those trading days and σ is the standard deviation.

To estimate the annual volatility of crypto asset, the number of Trading Days are set to 365, as opposed to 252 for the traditional stock market. In relation to the process of feature engineering, the trading days are established at 7, in order to determine the weekly volatility of Bitcoin and Ether. Calculating the rolling standard deviation using a 7-day window, excluding current day sales is a technique for approximating short-term sales volatility. This approach offers a flexible and dynamic measure that can facilitate the comprehension of recent trends and highlight potential risks or opportunities, and avoids data leakage.

In summary, these engineered features offer valuable perspectives on market behavior, potential manipulations, and the overall health and integrity of the trading environment. They condense complex interactions and activities into interpretable metrics, aiding both traders and regulators in making informed decisions. Properly designed features can illuminate nuances in the data, making models more insightful and predictive.

5.1.8 Feature Importance

The implementation of machine learning algorithms like XGBoost and Random Forest regressors requires attention to the quality and relevance of input features. They is a significant aspect of the model's performance. During the preliminary stages of model development, the feature engineering was restricted to minimal input, considering only the current values of variables without time lags. However,the models were not capable of capturing the temporal relationships within the data, which are often crucial in time-series forecasting tasks. Output of the model is the predicted daily sales. Inclusion of supplementary information obtained from the feature engineering task has the potential to enable the model to comprehend more intricate patterns. The vast number of features also considerably amplified the likelihood of overfitting.

5.1.9 Feature Selection

It is important to exercise caution when introducing new features to the dataset, as the benefits of enhanced performance must be weighed against the potential drawbacks of overfitting. A robust feature selection process is implemented to ensure that only the most relevant and informative features are utilized.

5.1.9.1 Average Method

Feature importance is calculated for both Random Forest and XGBoost regressors. For this experiment, all the engineered features are used. By averaging these importance values and retaining only those features with an importance greater than a set threshold (in this case, 0.00022), the feature set was effectively reduced to the 10 most significant features. This approach aims to simplify the model by focusing only on the most influential features, thereby reducing the model's capacity to overfit to the noise in the training data.

Feature
sales avg
Sales lag 1
Sales volatility
Trade Profit volatility
Supply
Trade Profit
Total bitcoin vol
Wash trade %
Buyer Seller lag 1
Trade Profit avg

Table 5.3: Features after averaging scores

Feature
Trade Profit
Total eth vol
Wash trade %
sales volatility
Sales lag 1
Gas price change %
Trade Profit volatility
ETH Price
Supply
Sales avg

Table 5.4: RFE Features

Table 5.3 lists the most importance features in descending order.

5.1.9.2 Recursive Feature Elimination

For both XGBoost and Random Forest models, recursive feature elimination (RFE) (see section 4.1.3.1) was employed to select the most impactful 10 features (Table 5.4. The models were subsequently retrained with this reduced and presumably more informative feature set, and the scores were recalculated. By doing this, RFE built a model exhibiting strong predictive power while reducing the risk of complexity, which is evident in the results.

5.1.10 Local Feature Importance

Local feature importance is performed using SHAPely explainer model coupled with a fitted regressor as discussed above. The SHAP values are resampled for different time windows to perform a period wise analysis.

5.1.11 Evaluation

To evaluate the effectiveness of the regression models, metrics like Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), R^2 score (`model.score`), Root Mean Squared Error (RMSE) are used from `sklearn.metrics`.

Machine learning algorithms like XGBoost and Random Forest Regressors require careful attention to the quality and relevance of input features, as this is crucial for their performance. Table 5.5 tabulates how both models performed with different combinations of features. The 'Train' and 'Test' scores are essentially the R^2 scores computed on the training and test data.

	Random Forest			
Metric	Minimal FE	All Features	Feature Avgs	RFE
Train Score	0.9833	0.99	0.99	0.99
Test Score	-1.00	-0.44	0.47	0.515
RMSE	13660089.58	12982125.95	7985792.18	7647178.29
MAE	10212385.70	9249659.63	5184706.21	5074547.30
MAPE	0.30	0.27	0.164	0.157
	XGBoost			
Metric	Minimal FE	All Features	Feature Avgs	RFE
Train Score	0.99	0.9996	0.99	0.99
Test Score	-0.87	-0.11	0.25	0.285
RMSE	12471223.39	10239656.98	9391525.65	9014481.49
MAE	9471140.74	7457512.10	6486490.55	6139721.07
MAPE	0.315	0.229	0.19	0.185

Table 5.5: Comparison of Random Forest and XGBoost Regressor Peformances

Initially, feature engineering focused on minimal input, ignoring time lags and volatility. This does not capture temporal relationships, which are essential in time-series forecasting tasks. In the context of regression, any negative values of the R^2 score (computed using the `model.score` method), indicate the model's inferiority compared to the reference. (The reference value is the variance in the test data itself.) This could be attributed to the model's failure to generalize any patterns in the data due to the absence of informative features that capture the relevant temporal dynamics.

To address this issue, feature engineering was carried out by increasing the dataset by creating additional features, such as 1-day lags, 7-day standard deviation (weekly volatility), 7-day rolling means, and crypto volatility. This increase enabled the model to understand more intricate patterns but also increased the likelihood of increased complexity, which is evident in the `All Features` column. The test score and MAPE for Random forest with all engineered features are worse than XGBoost's scores. It is important to exercise caution when introducing new features to the dataset, as the benefits of enhanced performance must be weighed against model complexity. Implementing a robust feature selection process is crucial to ensure only the most relevant and informative features are utilized.

Table 5.3 lists the most importance features in descending order. It is observed in table 5.5 that the model scores and error metrics have significantly improved in the last two columns. In terms of R^2 score, the Random Forest model performs better. XGBoost has a higher MAPE score as opposed to Random Forest, which means a higher error percentage. Recursive Feature Elimination with Random Forest performs better than XGBoost regressor in terms of Test score and MAPE. This could be attributed to Random Forest being less sensitive to minimal hyperparameter tuning.

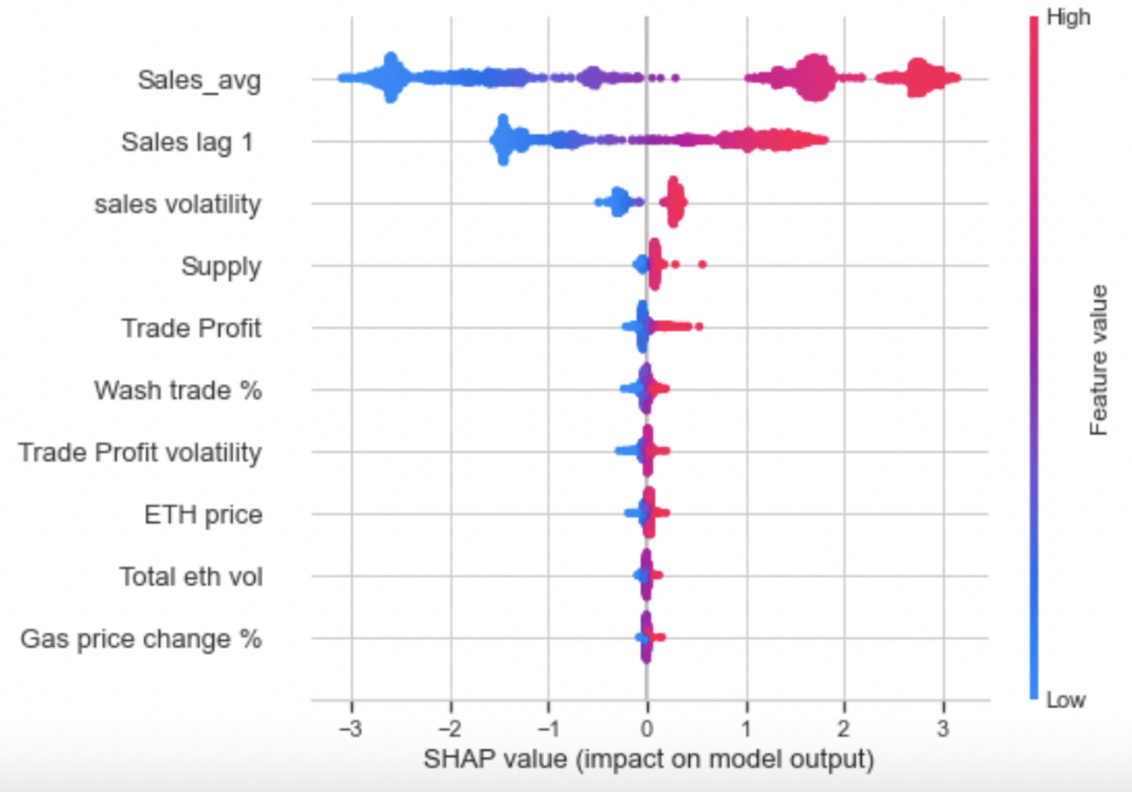

Figure 5.2: Global Feature Importance using SHAP (for Daily Sales (USD)

Figure 5.2 illustrates the nature of top features impacting target variable `Sales (USD)`.The SHAP feature importance results reveal significant insights into the factors that most influence the model's predictions. Intrinsic sales metrics, namely `Sales avg`, `Sales lag1`, and `Sales volatility`, emerge as critical determinants. The prominence of these features highlights the direct relationship between historical sales patterns and the predictive outcome. The `Sales avg` provides a smoothed representation of sales over time, which is pivotal for understanding baseline performance. `Sales lag1`, reflecting the previous day's sales, emphasizes the significance of immediate past performance. `Sales` volatility measures the variability or uncertainty in the sales figures, indicating the market's unpredictability. A higher sales volatility suggests fluctuating demand, which might be considered an indicator of market dynamics and consumer behavior.

Complementing these sales metrics are other significant features like `Supply`, `trade profit`, `Wash trade %`, `trade profit volatility`, `ETH price`, `Total ETH volume`, and `gas change%`. Trade profit sheds light on the profitability aspect, indicating how much revenue exceeds costs in trading activities. Its volatility mirrors the risk or stability associated with trading returns. Lagged `Wash trade%`, indicative of deceptive trading practices could signal market manipulation. Lastly, the inclusion of `ETH price` and `Total ETH volume` highlights the role of cryptocurrency (Ethereum in this case) in trading NFTs. These metrics depict the impact of crypto market and internal sales dynamics on the predictive outcome.

It is important to note that the target variable `Sales (USD)`, which is heavily skewed, is transformed to a logarithmic scale using `np.log`. This helps the target variable have a normal distribution. The predictions are in the log scale while using the log-transformed target variable. Re-transforming is performed to convert log-scale predictions to the original scale. An exponential function (inverse of the natural logarithm) - `np.exp()` is used for the same. It is imperative to execute this re-transformation when computing metrics such as the `MAPE` and the R^2 score to ensure that these metrics are comprehensible and comparable to models that were fitted to the untransformed target variable.

5.2 Feature Importance across time periods

While working with time series data, SHAP's local feature importance can be very useful in capturing the developing relevance of features at various temporal granularity. To find local importance, SHAP explainer is coupled with model with the best performance,i.e

Random Forest and RFE. By dividing the dataset into multiple time intervals like monthly, quarterly, biannually and yearly — it is possible to see the changing feature relevance and the varying influences on model outputs. For example, one factor may be crucial in determining forecasts one month but lose relevance the next month. Similarly, due to seasonality, macroeconomic fluctuations, or other external causes, characteristics may have different levels of relevance between quarters or years. By resampling and aggregating SHAP values throughout multiple durations, a thorough image of feature significance over time may be captured.

5.2.0.1 Monthly feature Importance

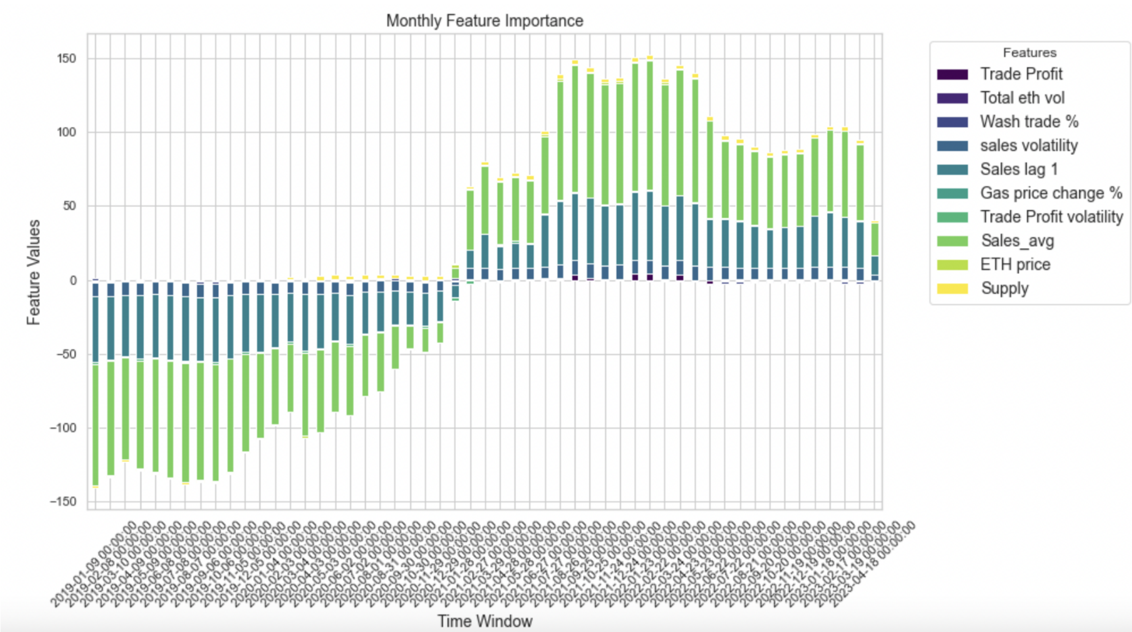

Figure 5.3: Monthly feature importance

Figure 5.3 depicts the significance of various features on a monthly basis. The graph clearly reveals that the weekly sales average is the most crucial feature, followed by sales lag and sales volatility. The adverse influence of trade profit volatility is noticeable in December 2020 and January 2021. Furthermore, from 2020 onwards, supply has a minor positive influence on sales. In January 2021, a diverse effect is apparent where the sales average has a favorable impact on daily sales, but sales lag, sales, and trade profit volatility still have an unfavorable impact. In May 2021, there is a marginal affirmative impact of Gas price change %, and from July 2021 onwards, the daily Ethereum price has a favorable effect on sales. Trade profit has a constructive impact for some months in 2021, and Wash Trade % has an almost negligible unfavorable impact in the latter part of 2022.

5.2.0.2 Quarterly feature Importance

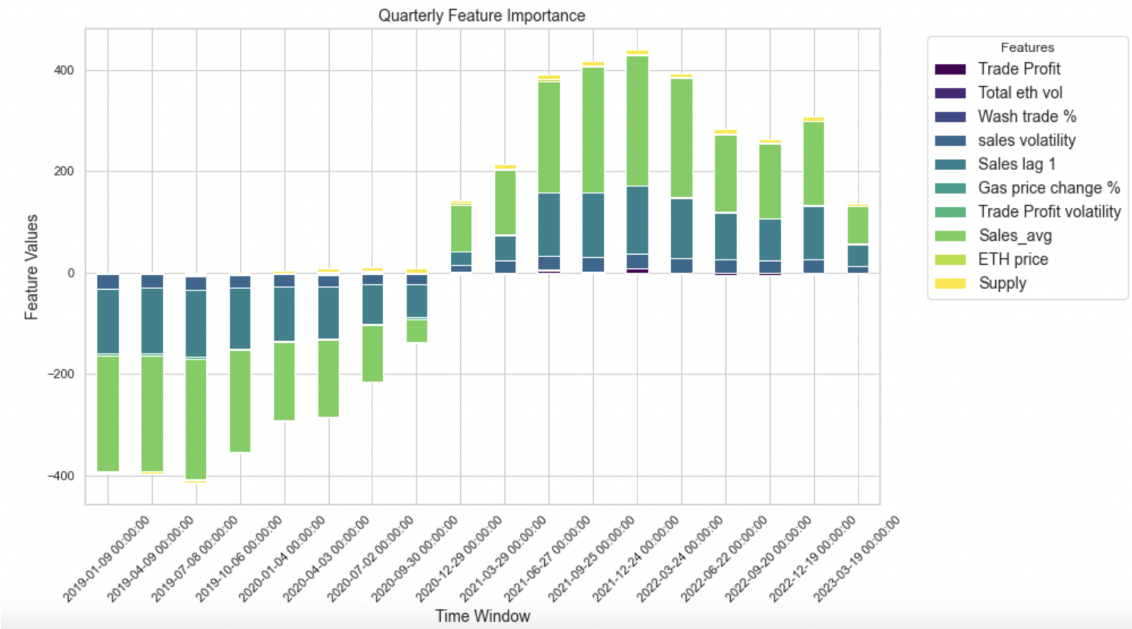

Figure 5.4: Quarterly feature importance

Figure 5.4 illustrates the feature importance on a quarterly basis. Volatility in Sales has a minor negative influence on sales until the fourth quarter of 2020 and a slight positive impact from 2021 onwards. From 2019 to the first quarter of 2020, the negative impact of lower sales average appears to increase slightly and then decrease. It will have a positive impact afterwards. The impact of previous day's sales is negative from 2019 to the last quarter of 2020, somewhat favorable for the next two quarters, and considerable thereafter. Trade profit has a somewhat negative influence, particularly in the last two quarters of 2022 and impacts favourably in the first two quarters of the same year. Supply has an overall positive impact in all quarters starting 2021. A slight positive effect of Ethereum price is seen in a few quarters of 2021 and 2022.

5.2.0.3 Biannual feature Importance

Figure 5.5 illustrates the feature importance for every 6-month period. Sales average, sales lag, and sales volatility all have a negative influence on reducing orders in 2019. These

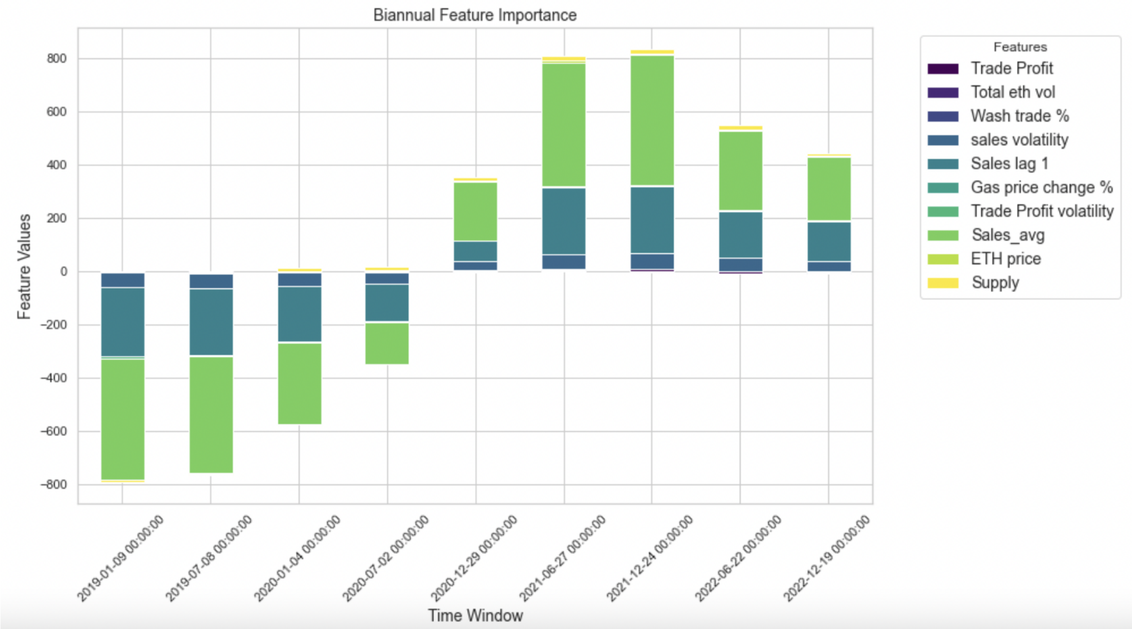

Figure 5.5: Bi-Annual feature importance

factors have a favorable influence in the latter half of 2021. This could be attributed to sales picking up in the latter half of the year. Similar positive patterns can be seen beginning in the second part of 2021. In both halves of 2022, trade profit has a minor negative influence. Supply has a slight favourable impact on sales 2021 onwards.

5.2.0.4 Annual feature Importance

Figure 5.6 illustrates the feature importance for every year from 2019 to 2023. It is worth noting that sales were quite stable from 2019 to the first half of 2020. Volatility began to rise in 2021. Sales volatility, sales average, historical sales volatility, and trade profit all have a negative influence in 2019. 2020 follows a similar trend, with suppl having a positive effect. Only sales volatility, sales average, and lag sales have a strong beneficial influence after 2020. Supply and Ethereum price have a modest positive influence during the same years.

5.3 Search Interest and Volatility

The setup for this experiment includes checking the stationarity of data, cointegration and causal relationships.

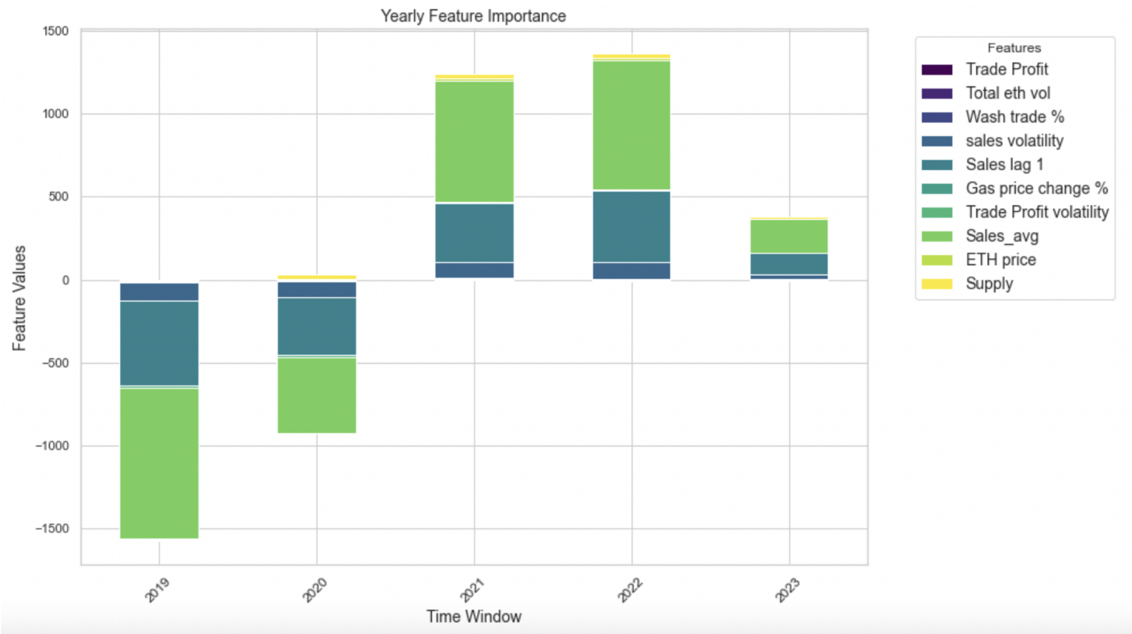

Figure 5.6: Annual feature importance

5.3.1 Data

The data for weekly Sales analysis is obtained by finding the average sales every week. The search interest data is obtained from Google Trends (64). Google Trends offers access to an unfiltered sample of search requests targeted to Google. The information is anonymised and categorized to fit to a topic of the query. The search data is normalized to simplify analysis. The output in an interactive graph, where the relative number of searches for specific term to the total number of Google searches are shown. Figures on the graph do not represent absolute search volume numbers due to the normalization process. The information, on the other hand, is plotted between 0-100.

To obtain Google Trends data, multiple search words have been used. They are classified into four categories - "Neutral Phrases", "Basic", "Positive" and "Negative". Table 5.6 list the keyword categories and associated keywords. Search interest for every category is calculated by taking the mean of search interest of all the keywords.

`Basic` keywords include terms that are fundamental aspects or features associated with the topic. `Neutral Phrases` are more specific or focused terms related to the topic which have a neutral sentiment but are likely to reflect a more engaged level of interest. They are coined by clubbing `Basic` with other phrases. `Negative` phrases are terms that people

Search Type	Keywords
Basic	'blockchain', 'ethereum', 'bitcoin', 'nft','cryptocurrency'
Neutral Phrases	'bored ape yatch club nft','cryptozoo nft', 'nft bored ape', 'nft discord', 'nft marketplace', 'opensea discord', 'opensea nft', 'twitter nft','opensea marketplace'
Negative	'is nft a scam', 'nft scam', 'nft wash trading', 'wash sale crypto', 'rug pull nft', 'opensea phishing','wash sale crypto','twitter giveaway', 'nft giveaway','free nft','crypto giveaway twitter'
Positive	'buy nft', 'sell nft', 'NFT future', 'NFT guide', 'NFT investment'

Table 5.6: Classification of search terms

search for when there is an issue with a topic of interest, or when they are looking for criticisms or downsides. `Positive` keywords include searches which have a positive and hopeful sentiment towards the NFT market.

5.3.2 Stationarity

A time series is stationary if its statistical properties (mean, variance) do not change over time. The Augmented Dickey-Fuller test is used to check the unit root of a time series. A unit root refers to a time series property that indicates non-stationarity.

$$H_0\text{: Time series is non-stationary.}$$
$$H_A\text{: Time series is stationary (has unit root).}$$

If the p-value is significant (>0.05), the null hypothesis is not rejected. Table 5.7 give the ADF statistics before and after differencing the data.

It is observed that all features in the original time series are not stationary, since the p-value is greater than 0.05. The data is differenced, and the series is now stationary, as evident in the table.

	Original Time Series		Post Differencing	
	ADF	p-value	ADF	p-value
Sales (USD)	-2.32	0.165	-13.682	0
Neutral Phrases	-2.042	0.268	-4.726	0.000075
Basic	-1.897	0.333	-6.561	0
Positive	-1.728	0.416	-6.848	0
Negative	-2.169	0.217	-15.588	0
ETH Volatility	-1.505	0.53	-8.13	0
BTC Volatility	-1.758	0.401	-8.735	0

Table 5.7: Unit Root Tests for non-stationary and stationary data

5.3.3 Cointegrations

The Johansen cointegration rank test is a statistical method that aids in the identification of cointegration relationships within multiple time series variables. Notably, the test accounts for the probability of there being more than one cointegrating relationship. This method provides a reliable means of assessing the long-run equilibrium between variables.

The Johansen test is used to determine the number of cointegrating vectors in non-stationary time series data. There are two different likelihood ratio tests to determine the number of cointegrating vectors - Trace test and Maximum Eigenvalue.

Hypotheses for Trace test :

H_0: Number of cointegrating vectors is r.
H_A: Number of cointegrating vectors is more than r.

Hypotheses for Max Eigenvalue test :

H_0: Number of cointegrating vectors is r.
H_A: Number of cointegrating vectors is $r + 1$.

r_0	r_1 test	Test Statistic	Critical Value
0	7	395.3	150.1
1	7	276.7	117.0
2	7	177.2	87.77
3	7	100.7	62.52
4	7	39.26	41.08

Table 5.8: Trace Test Statistic

r_0	r_1 test	Test Statistic	Critical Value
0	1	118.6	55.82
1	2	99.48	49.41
2	3	76.51	42.86
3	4	61.44	36.19
4	5	21.64	29.26

Table 5.9: Maximum Eigenvalue Test

For both tests, the null hypothesis is typically rejected if the computed test statistic is greater than a critical value, which is determined by the tests. $\mathbf{r}_0$ and $\mathbf{r}_1$ are the null and alternate hypotheses respectively. Upon conducting trace (Table 5.8) and maximum eigenvalue (Table 5.9) tests, the null hypothesis cannot be rejected for the first four variables as their test statistic exceeds the critical value. However, the fifth variable yields a test statistic value which is lower than the critical value, thus indicating the rejection of the null hypothesis. Hence, the maximum number of cointegrating variables is determined to be four.

5.3.4 Vector Error Correction Model

Lag	AIC	BIC	FPE	HQIC
0	66.71	67.57*	9.373e+28	67.06*
1	66.61	68.23	8.502e+28	67.26
2	66.41	68.77	6.949e+28	67.36
3	66.39	69.52	6.903e+28	67.65
4	66.31*	70.18	6.393e+28*	67.87

Table 5.10: VECM Order Selection (* highlights the minimums)

Since the data in raw form is non-stationary and there exist cointegrated variables, Vector Error Correction Method is used to analyse the time series. A VECM model is fit on the non-stationary data to select the optimal number of lags. Table 5.10 contains the VECM model summary. One widely-used criterion for this selection is the Akaike Information Criterion (AIC). The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Information Criterion (HQIC), and Final Prediction Error (FPE) are statistical measures used for model selection. The AIC balances the model fit against its complexity, penalizing models with a large number of lags to avoid overfitting. BIC and HQIC have the least values, but they are at lag 0. Since lag 0 does not give any temporal information, we choose a lag with the values which have the least AIC. Hence, the optimal number of lags are 4.

5.3.4.1 Durbin Watson

Durbin Watson is a statistical method to account for autocorrelation in residuals. Residuals in question are obtained after fitting the VECM model.

H_0: There is no correlation among the residuals.
H_A: The residuals are autocorrelated.

Feature	Test Statistic
Sales (USD)	2.06
Neutral Phrases	2.06
Basic	2.05
Negative	2.04
Positive	2.08
Eth Volatility	2.0
Btc Volatility	1.92

Table 5.11: Durbin-Watson Test Statistic

The test statistic takes values between 0 and 4. If the value is close to 2, there exist no autocorrelations. It is evident from table 5.11 that there are no autocorrelations among variables.

5.3.5 Granger Causality

When applied in the context of a Vector Error Correction Model (VECM), the Granger causality test helps determine the direction of causality between integrated variables that share a long-run equilibrium relationship. The method `test_granger_causality` applied on a fitted VECM model tests for Granger causality - whether the lags of one variable (or set of variables) Granger-cause another variable within the VECM framework. There were four lags in this case. The test statistic usually follows a chi-square distribution under the null hypothesis.

H_0: Lagged X does not Granger-cause Y.
H_A: Lagged X Granger-causes Y.

The Granger causality test on the fitted Vector Error Correction Model (VECM) for 4 lags aims to determine whether past values of one variable can predict future values of another variable. Table 5.12 contains p-values associated with Granger causality tests between different variable pairs. The header row represents the lagged variables, and header column denotes the predictor variable. p-value < 0.05 means the lagged variable 'Granger-causes' the dependent variable.

`Sales (USD)`, `Neutral phrases` and `Negative` are Granger-caused by `Positive` sentiment, given the p-values are below 0.05. In contrast, none of the lagged variables are found to have a Granger-causal effect on `Basic`. Additionally, the variable of `ETH Volatility` is Granger-caused by all variables except `Negative`, while `BTC Volatility` is Granger-caused by all variables except `Eth Volatility`.

	Sales (USD)	Neutral Phrases	Basic	Negative	Positive	ETH Volatility	BTC Volatility
Sales (USD)	1	0.46	0.47	0.86	0	0.88	0.3
Neutral Phrases	0.45	1	0.19	0.96	0	0.42	0.52
Basic	0.28	0.41	1	0.12	0.22	0.19	0.28
Negative	0.16	0.06	0.23	1	0.04	0.28	0.16
Positive	0.02	0.01	0.25	0.19	1	0.07	0.34
Eth Volatility	0	0.04	0	0.28	0	1	0.02
Btc Volatility	0	0.02	0	0.13	0.17	0.03	1

Table 5.12: Granger causality values for various variable pairs.

It could be concluded that volatility in Bitcoin could lead to Ethereum volatility, not vice-versa. This phenomenon could be attributed to the fact that the Bitcoin market boasts a larger size as opposed to Ethereum (65). Furthermore, it has been noted that a positive sentiment within the context of the NFT market has the potential to significantly impact sales and also cause Ethereum volatility. Similarly, a neutral sentiment towards the same market could have a similar effect. It is worth noting that the variables mentioned above are not impacted by negative sentiment.

5.4 Anomaly Detection using STL Decomposition

Sales figures, often used as a barometer for a business's success, can fluctuate, might result from a myriad of factors. Therefore, identifying anomalies in sales data is essential to understand market dynamics. For this analysis, daily sales data (in USD) were examined spanning five years from 2019 to 2023.

The data considered is univariate, and no other potential influencing factors were considered. The distribution of sales does not follow a common pattern. At a holistic level, the series displayed minimal seasonality or overarching trends. This means consistent patterns repeating over specific intervals or long-term upward or downward movements were not pronounced. Some consistency in trends were found when the STL decomposition was performed on a yearly basis. The residuals were found to not follow a normal distribution. An alternative estimator of scale S_n, with a constant 1.1926 was used to find upper and lower thresholds to detect anomalies. Figure 5.7 is an example of STL Decomposition for a single year 2021.

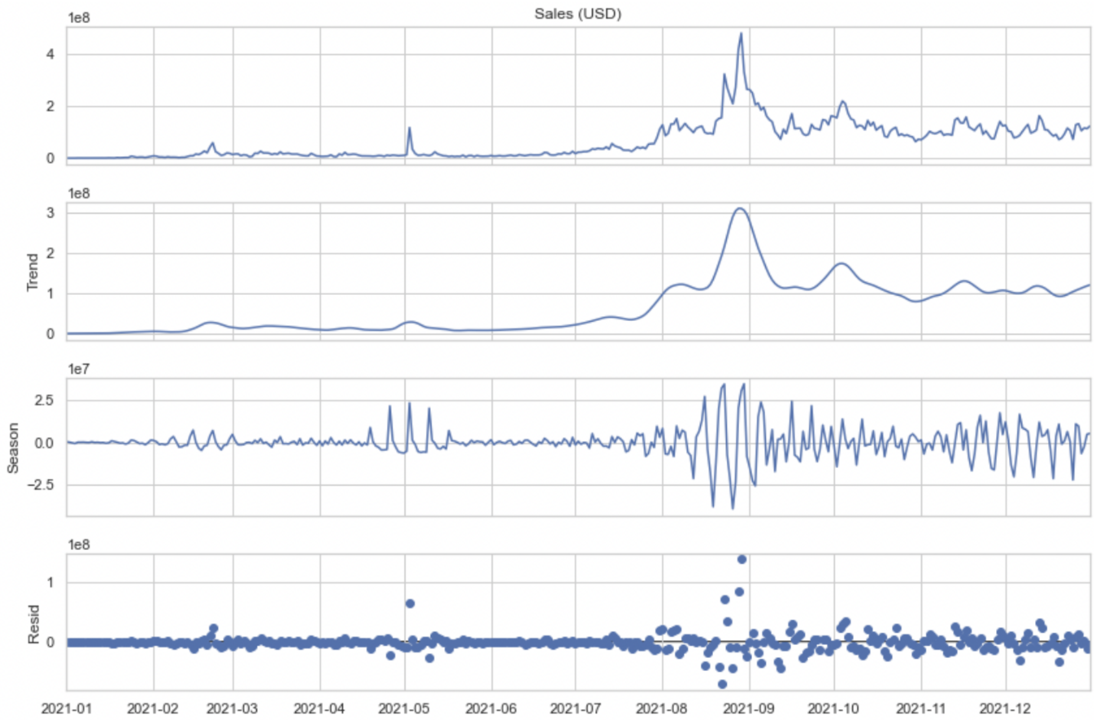

Figure 5.7: Example STL Decomposition for a year (2021)

Figure 5.8 illustrates the anomalies found in 2021.

To detect anomalies, STL decomposition has been used on daily sales data for every year from 2019 to 2023. The results are then combined and juxtaposed against the entire daily sales data in figure 5.9. If the STL residuals are more than the stated threshold, the anomaly is positive. Otherwise, it is negative. Note that positive and negative anomalies are attributed to spikes and dips in daily sales. These terms will be used interchangeably in the study. Between the years 2019 and 2020, there were only a meager number of positive anomalies detected. This could be attributed to the nascent nature of the NFT market and also lower volatility in sales. The classification of an anomaly as positive or negative is based on its relationship with upper and lower thresholds. Anomalies (positive and negative) can be detected during the latter half of 2021 and the former half of 2022.

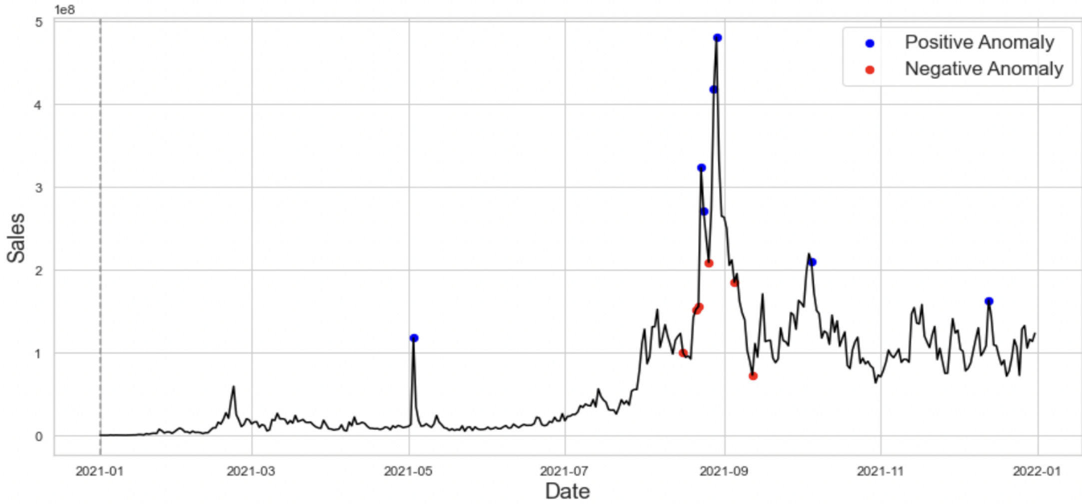

Figure 5.8: Anomalies in Sales (2021)

In 2023, there is a solitary positive anomaly that is detected.

Using local feature importance from SHAP 5.2, the nature of anomalies are determined.

Figure 5.10 visually represents the significance of the intrinsic features impacting positive sales anomalies. The legend encompasses all the features considered for SHAP analysis. The x-axis of the plot contains the dates of anomaly occurrence. Notably, `Sales Average` and `Sales lag` stand out as the primary factors leading to positive anomalies. Additionally, `Sales volatility` is a notable factor. The feature importances follow a similar pattern as above - there is a negative impact of the major factors till 2020 and take a positive magnitude afterwards.

Figure 5.11 visually represents the significance of the external factors impacting positive sales anomalies. The first positive anomaly in 2019 see a high positive impact by `Supply` and a negative impact by `ETH Price`. `Trade profit volatility` and `Gas price change %` have a slight positive impact in the anomalies found in 2021 onwards. `Trade profit` is one of the more important factors, which takes a positive and negative impact for different anomalies. `Supply` is consistent with its positive impact. `Wash Trade %` sees a positive impact till the latter part of 2021 and a slight negative impact afterwards.

Figure **??** also visually represents the significance of intrinsic features impacting negative sales anomalies. The behaviour of features for negative anomalies is slightly different.

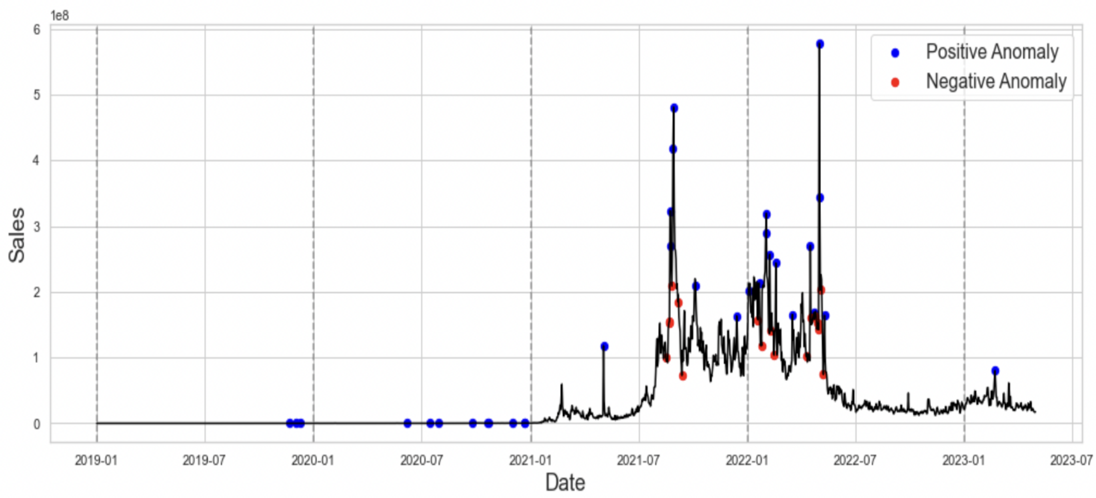

Figure 5.9: Anomalies in daily Sales

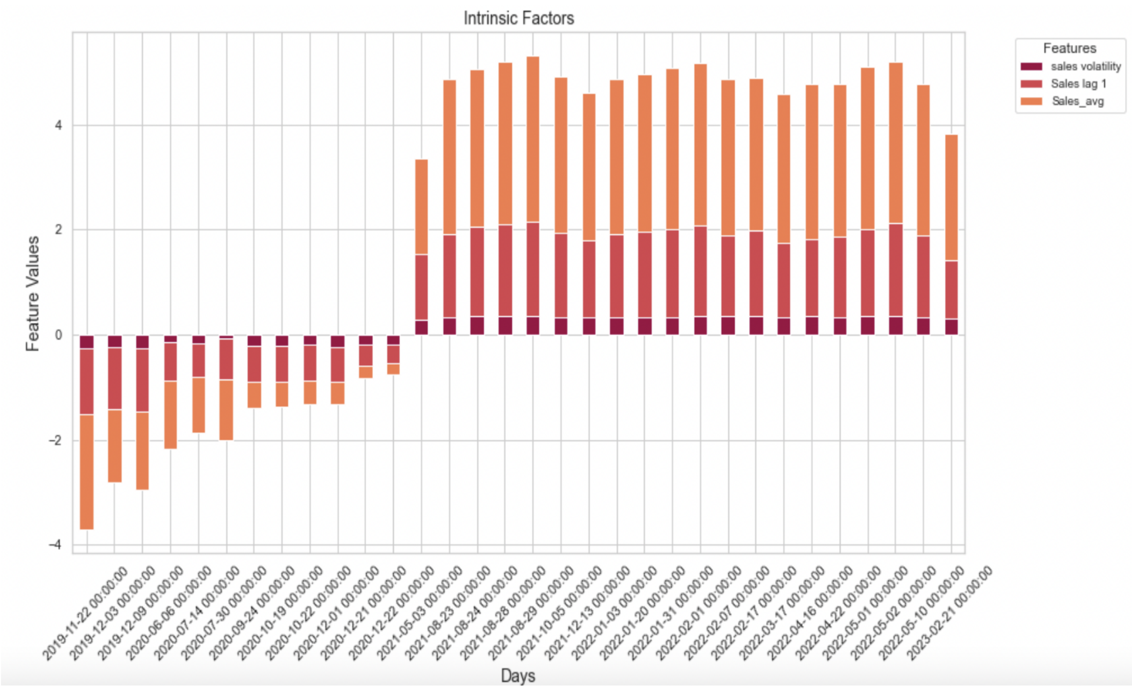

Figure 5.10: Intrinsic Factors for Positive Sales Anomalies

Intrinsic sales factors like `Sales average`, `Sales lag` and `Sales volatility` have positive impacts in descending order.

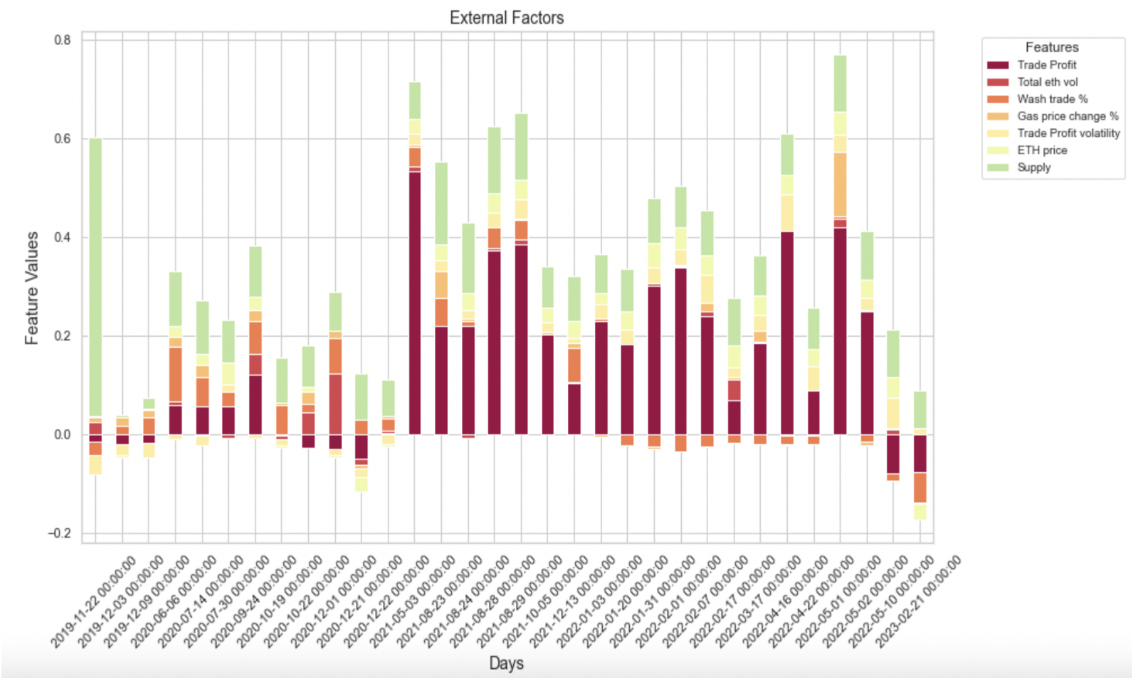

Figure 5.11: External Factors for Positive Sales Anomalies

There are hints of positive impact by `Supply`, `Trade profit volatility` and `Ethereum Price`. `Trade Profit` has significant positive and negative impacts. `Wash Trade%` has positive effects in the first half of 2021 and negative impact thereafter (Figure 5.13).

Features	F1	F2	F3	F4	F5	F6	F7	F8	F9
ETH price	0	0	0	0	0	10	12	5	2
Gas price change %	0	0	0	0	1	0	4	6	10
Sales lag 1	6	26	0	0	0	0	0	0	0
Sales_avg	26	6	0	0	0	0	0	0	0
Supply	0	0	2	7	20	2	0	0	1
Total eth vol	0	0	0	1	1	0	5	0	11
Trade Profit	0	0	5	14	5	3	2	1	1
Trade Profit volatility	0	0	0	1	2	7	6	10	4
Wash trade %	0	0	0	2	3	10	3	10	3
sales volatility	0	0	25	7	0	0	0	0	0

Table 5.13: Feature Counts for Positive Anomalies

Table 5.13 gives the count of important features for positive anomalies. The most im-

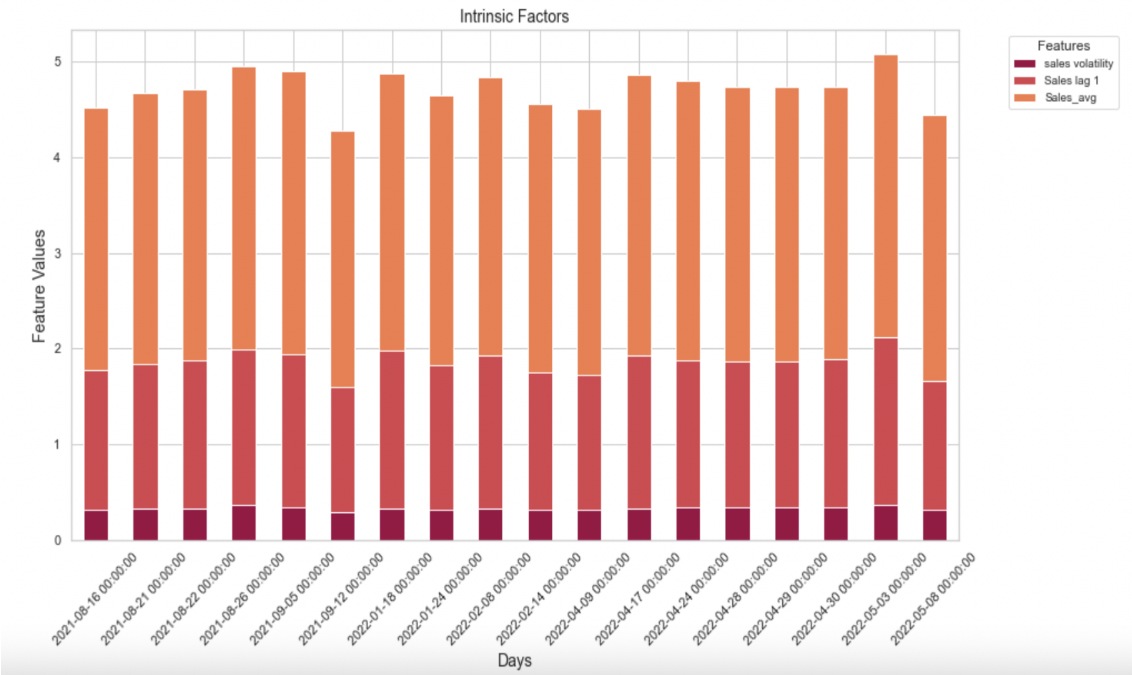

Figure 5.12: Intrinsic Factors for Negative Sales Anomalies

portant features are `Sales average` and `Sales lag`. `Sales Volatility`, `Trade Profit` and `Supply` are third most important features.

Features	F1	F2	F3	F4	F5	F6	F7	F8	F9
ETH price	0	0	0	0	7	10	1	0	0
Gas price change %	0	0	0	0	0	2	2	3	10
Sales lag 1	0	18	0	0	0	0	0	0	0
Sales_avg	18	0	0	0	0	0	0	0	0
Supply	0	0	0	15	3	0	0	0	0
Total eth vol	0	0	0	0	0	0	4	6	5
Trade Profit	0	0	0	3	6	1	1	1	0
Trade Profit volatility	0	0	0	0	1	4	7	6	0
Wash trade %	0	0	0	0	1	1	3	2	3
sales volatility	0	0	18	0	0	0	0	0	0

Table 5.14: Feature Counts for Negative Anomalies

Table 5.14 gives the count of important features causing negative anomalies. `Sales average` and `Sales lag` and `Sales Volatility` are the top 3 undisputed features. They

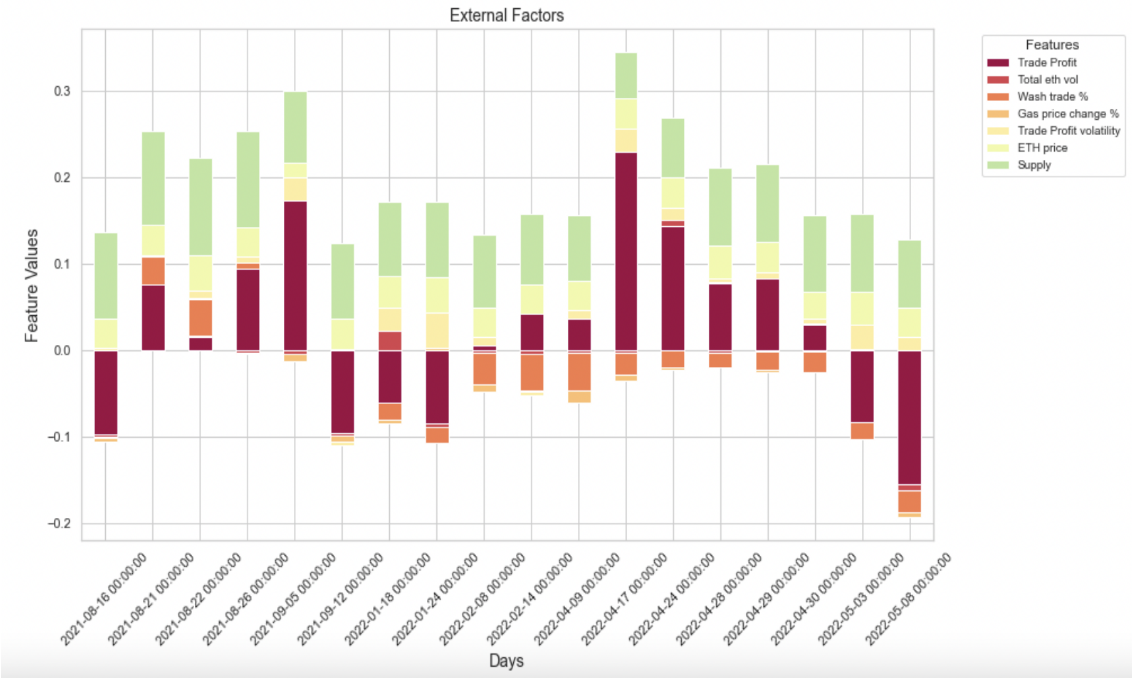

Figure 5.13: External Factors for Negative Sales Anomalies

are followed by `Supply`, `Trade Profit` and `Etherum price`.

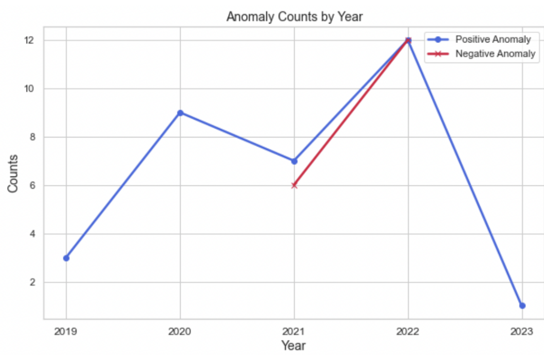

Figure 5.14: Anomaly Counts (Years)

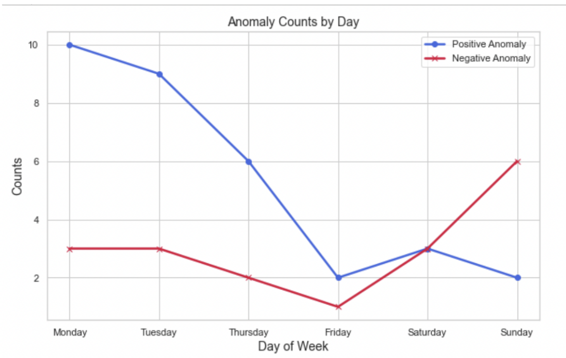

Figure 5.15: Anomaly counts (Day)

The above figures illustrate the count of anomalies across different years and days of the week. The total number of anomalies identified are 50, with 32 positive and 18 negative anomalies.The data indicates an evolving trend in the NFT market over the years. Starting from 2019, there was an increasing trend in positive anomalies, suggesting growing interest or perhaps market fluctuations that favored NFT trades. However, the slight decrease in 2021 might indicate market adjustments or external factors that momentarily dampened this growth. The year 2022 stands out marking the peak for both positive and negative anomalies. This implies a year of heightened volatility, with potential swings in market sentiment, investments, and other influential factors. The presence of negative anomalies exclusively in 2021 and 2022 signals periods of potential market challenges or downturns. By 2023, the solitary positive anomaly, combined with the absence of negative ones, hints at the NFT market stabilizing. The limited data for 2023 advises against drawing definitive conclusions for the entire year.

Figure 5.4 contains the anomaly counts for different days of the week. The absence of anomalies on Wednesday could suggest a mid-week stability. The maximum number of positive and negative anomalies occur on Monday and Sunday respectively. Count of both anomalies reach a minimum on Friday and pick up slightly during the weekend. Given that NFTs deviate from traditional stock markets by trading seven days a week, the day-wise anomaly distribution highlights the importance of understanding daily dynamics while assessing market behavior.

6

Discussion

The primary objective of this study was to conduct a comprehensive investigation of the dynamics of NFT market using four distinctive lenses. Firstly, the aim was to study factors impacting daily NFT sales. Global feature importance was determined by using XGBoost and Random Forest regressors. Feature selection was then performed to select the pertinent features. The best model was then chosen to extract local feature importance, using SHAPely. Secondly, Finding local importance facilitated a nuanced analysis of influential factors impacting daily sales across varying time windows. Thirdly, search interest, crypto volatility, and weekly sales were examined using Vector Error Correction Models (VECM) and Granger causality tests. Studying the interaction between these variables provided insights into market sentiment and potential buying triggers. This approach sought to highlight the impacts of lagged variables on prospective predictions. Lastly, anomalies in daily sales were detected to understand unusual patterns. Studying factors causing these anomalies helps in understanding underlying reasons, enabling timely interventions or capitalizing on new opportunities. Furthermore, differentiating between positive and negative anomalies stakeholders to replicate success or prevent recurring issues, ensuring consistent investment strategies. To detect anomalies within daily sales patterns, Seasonal-Trend Decomposition (STL) was used.

6.1 Feature Importance Analysis

When examining the dynamics of the NFT market, feature importance can be a valuable tool both on a global and local scale. To identify the key variables driving this market, two regressors - Random Forest and XGBoost - were initially employed with baseline features, which were then supplemented with new features designed to capture temporal information. The Recursive Feature Elimination algorithm was implemented to identify the most efficient features for further analysis. To extract local feature importance, a SHAPely explainer model was used. As a result, this analysis has highlighted the significance of several intrinsic sales attributes - specifically, sales volatility, weekly sales average, and lagged sales - in driving market dynamics. It is noteworthy that these intrinsic sales features were found to be more consequential than extrinsic attributes such as Ethereum and Gas prices.

The assessment of market performance can be viewed through two different perspectives: the weekly sales average and lagged sales. While the former offers a short-term perspective, the latter provides historical context, which is crucial in identifying relevant patterns and predicting future movements. The direct market activities inherent in these features contribute significantly to the model's overall importance. However, external variables such as Ethereum price may not be directly correlated with NFT sales, but they play a pivotal role nonetheless. NFT sales are influenced by various factors, including trade profit, supply, and wash trade percentage, albeit to a lesser extent.

The usage of absolute feature importance might have left out some variables with negligible importance, suggesting that a relative feature importance approach could offer a more comprehensive understanding of variable contributions.

6.2 Feature Importance over Different Time Windows

Notably, intrinsic sales variables such as sales average, lagged sales and sales volatility have retained a negative trajectory up until 2020. Furthermore, Supply has had a slightly positive impact on sales across all periods from 2019. January 2021 displays a diverse impact of factors, with sales average having a positive influence on daily sales. In addition, trade profit has a minor negative influence on sales in 2022 and 2023. This observation may indicate a wider shift in the NFT market landscape during this period. One plausible assumption is that the global pandemic has influenced digital markets, leading more users towards digital and decentralized platforms. This hypothesis has not been quantified in the study.

6.3 Search Interest, Volatility and Sales

The VECM model with Granger causality revealed interesting interactions. It became evident that Bitcoin's market activities can cascade effects onto Ethereum, likely due to Bitcoin's larger market share and dominant positioning in the crypto space. Furthermore, the strong influence of positive sentiment on Ethereum volatility and NFT sales highlights the importance of market sentiment in influencing trading activities. Paradoxically, the analysis indicates that positive and neutral sentiments can spur negative sentiment. It could be concluded that the NFT and crypto market is sentiment-driven. It is important to acknowledge that the Granger causality test suggests predictive power and not exact causation.

6.4 Anomaly Detection in Sales Data

Detecting anomalies in daily sales data is critical for comprehending anomalous market activity, which may have been caused by external shocks. Using 'Sales (USD)' as a univariate time series enables more focused study on sales without being distracted by other factors.

The consistent significance of Sales average, lagged sales and sales volatility in both positive and negative anomalies highlight their fundamental role in understanding sales patterns. Features like Supply and ETH price have an influence across various importance levels, pointing to their crucial insights on broader market dynamics. Wash trade% is more prominent for increase in sales , as it indicates hints of inflated trades. Supply and Ethereum daily price shift in their importance between increased and decreases sales, with supply being more prominent in decreased sales. Trade Profit and its volatility give a moderate perspective on positive anomalies but are significant for negative ones. Notably, the importance of Gas price change % varies between both anomaly types, emphasizing the need to dig deeper into its function in sales data.

It could be concluded that intrinsic sales factors have a negative impact on increase in sales till the beginning of 2021, and a positive impact thereafter. External factors like Supply, Trade Profit and Ethereum price mostly have a high positive impact. An increased supply and trade profit contributed to more sales. A dip in the Ethereum price importance could be attributed to it being the native currency in which NFTs are traded. For decrease in sales, intrinsic factors have a high positive impact. Negative importances of trade profit and Wash trade% also lead to a dip in sales.

The study identified 50 anomalies, out of 1581 data points - comprising of 32 positive and 18 negative anomalies. They reflect the changing dynamics of the NFT market over the years. 2019 witnessed a surge in positive anomalies, indicative of an increasing interest in NFT trades. However, a decline in 2021 hints at potential market adjustments. 2022 emerges as a pivotal year, exhibiting peaks in both anomaly types, suggesting heightened market volatility influenced by various factors. On performing a 'day of the week' analysis, it is found that Wednesday is devoid of any anomalies. Positive and negative anomalies peak on Monday and Sunday respectively. There is a dip on Friday, with a resurgence during the weekend,

This discussion does not delve into specific reasons, but events like significant developments in the NFT space, shift to Ethereum 2.0, global economic shifts, regulatory reforms,etc, might have led to the increased volatility. One of the drawbacks associated with the utilization of STL is its inadequate ability to effectively handle irregular trends. Additionally, the lack of validation represents another limitation. Its performance is enhanced by breaking down the dataset into smaller time periods. Alternatively, other algorithms, such as Isolation Forest, Principal Component Analysis, and Local Outlier Factor, could be utilized. However, one disadvantage of these alternatives is that the fraction of outliers, also known as contamination factor, must be predetermined. On the other hand, STL utilizes statistical techniques to detect anomalies (section 5.4), which is a more reliable approach.

7

Conclusion

This thesis provides a comprehensive examination of the factors influencing daily NFT sales. Through feature importance analysis, it is found that intrinsic sales attributes, supply, trade profits and daily Ethereum price are primary drivers of these sales. In terms of technical analysis, Recursive Feature Elimination (RFE) technique, coupled with Regression models like Random Forest and XGBoost, has been instrumental in isolating and understanding feature importance. SHAPely further dissects feature importance for every data point.

Furthermore, this study has shed light on the symbiotic relationship between public perception and market dynamics by examining the correlation between public interest, weekly NFT sales and crypto volatility. For this purpose, a VECM (Vector Error Correction Model) is fit on non-stationary data involving cointegrations. By utilizing Granger causality, the influence of positive sentiment on Ethereum's volatility and its direct impact on NFT sales is identified. The results highlight the sentiment-centric nature of the NFT and crypto market.

The identification of anomalies in daily sales using STL, aided by the SHAPely local feature importance method, emphasizes the need for continuous monitoring and understanding of NFT sales patterns. 2022 marked the year with most anomalous trades. Sales average and lagged sales were major drivers of anomalous trades, followed by sales volatility, daily supply of NFTs, Ethereum price and trade profits.

- **RQ1 : What are the most important factors driving NFT sales?**

  Intrinsic sales attributes (weekly sales average, lagged sales (1-day) and weekly sales volatility) are the most important factors driving NFT sales. While external variables such as Ethereum price and daily NFT supply may not be the most important predictors for NFT sales, they play a pivotal role nonetheless. These factors are pivotal as an increased supply leads to more transactions, and hence more sales. Ethereum daily price is also important as NFT transactions take place using ETH. NFT sales are influenced by various other factors, including trade profit, wash trade percentage, and gas price change percentage, although to a lesser extent.

- **RQ2 : How to identify factors impacting sales across different time windows?**

  Regression methods like Random Forest and XGBoost are used as explainer models to find global feature importance. Recursive Feature Elimination (RFE), coupled with the best performing model (Random Forest), is used to find global and local feature importance. SHAP local feature importance is then calculated using the explainer model. The data is resampled for different time windows like 30 Days, 90 Days, 180 Days and 365 Days and important features are determined.

- **RQ3 : How do market sentiment, crypto volatity and NFT market interact with each other?**

  Using VECM and Granger causality, it is evident that Bitcoin's market activities can have a cascading impact on Ethereum, which could be attributed to its larger market share and dominant position in the crypto space. Additionally, the analysis highlights the significance of market sentiment in influencing trading activities. Paradoxically, positive and neutral sentiments potentially Granger-cause negative sentiment. Despite this, it is important to note that the Granger causality test only suggests predictive power and not exact causation, highlighting the sentiment-driven nature of the NFT and crypto market. Weekly NFT sales are found to have an impact on Positive market sentiment. Additionally, these sales are found to Granger-cause both bitcoin and ethereum volatility. This observation highlights the impact of NFT sales on cryptocurrency market trends.

- **RQ4 : To what extent could anomalies in daily NFT sales be attributed to specific internal or external factors?**

  The identification of anomalies in NFT sales can be achieved through the application of Seasonal Trend Decomposition. Upon identification, a thorough analysis of the factors driving these anomalies is conducted, revealing that intrinsic sales features including volatility, average, and lag, have a significant impact on sales. External variables like Ethereum and Gas prices, daily NFT Supply also are prominent, albeit on a smaller scale. While algorithms such as Isolation forest and PCA require a predetermined fraction of outliers, the use of STL is a more suitable alternative.

This is due to the fact that STL employs residuals and statistical tests to compute a threshold for the detection of anomalies.

The research question **How do external market forces and overall public opinion together shape the trends and patterns in NFT sales?** is answered using aforementioned methods. Intrinsic sales features have a negative impact on daily sales till the beginning of 2021, and high positive impact thereafter. External factors like Ethereum price, supply, trade profits have different levels of impact over times, albeit on a smaller scale. Weekly NFT sales (lagged 4 weeks) are found to Granger-cause current positive market sentiment and crypto volatility. Positive market sentiment (lagged 4 weeks) is also found to Granger-cause weekly NFT sales.

7.1 Future Work

The study faces three key limitations that warrant further exploration. Firstly, it makes use of absolute feature importance metrics, potentially sidelining nuanced variables with relative importance in the daily sales of NFT marketplaces. This approach may miss significant interactions between less prominent factors, diminishing the model's predictive or descriptive efficacy. Secondly, the STL decomposition used for time-series analysis has not been validated, leaving uncertainties around the reliability of the anomalies identified. Thirdly, variables in the given dataset might not be the most explainable features to predict sales. Every component within it is highly volatile, and external events like the FTX crash, Global Pandemic, switch to Ethereum 2.0 and change in regulations are not taken into account or quantified.

For future work, incorporating relative feature importance could provide a more intricate understanding of variables affecting daily NFT sales, and may even reveal previously overlooked interactions. With the current features, evaluation metrics could be improved by hyperparameter tuning. Neural network models like LSTM, 1D Convolutional Neural Network and Attention mechanisms could be better suited for a volatile dataset with a temporal component. Additionally, rigorous validation methods for STL decomposition should be introduced to ensure the reliability and applicability of these components. This will not only enhance the robustness of the research but also offer a more comprehensive insight into the variables and dynamics driving the NFT market.

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