University of Brasília

Exact Sciences Institute
Computer Science Department

# Exploring Anomaly Detection Techniques to Identify Fraudulent Cryptocurrency Transactions: A Case Study at Mercado Bitcoin

Kevin S. Araujo

Dissertation submitted in partial fulfillment of the requirements to
Professional Master's Degree in Applied Computing

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Brasília
2023

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# Dedicated to

The dedication section is where the writer expresses gratitude or others, normally those who have inspired or assisted them in their research and writing. It is usually the shortest page of an academic paper.

# Acknowledgements

Thanks to Google and Wikipedia.

# Abstract

*Mercado Bitcoin, a Brazilian cryptocurrency exchange, has facilitated over 50 billion reais in trading since 2013, offering +200 assets to more than 3.7 million clients. Recent attention has triggered a surge in cryptocurrency-related fraudulent activities, primarily due to its inherent anonymity. Financial market abuse, detrimental to market functioning, occurs in three main categories: information-based manipulation, action-based manipulation, and trade-based manipulation [1]. Trade-based abuse often involves price manipulation, specifically targeting equity bid/ask prices [1, 2]. This research focuses on the category of market manipulation known as price manipulation. Using anomaly detection tools, we will analyze post-trading phase public data from Mercado Bitcoin API to identify and flag anomalous transactions. Subsequently, a back office analysis will determine the fraudulent nature of these transactions.*

**Keywords:** criptocurrencies, anomaly detection, machine learning

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# Chapter 1

# Introduction

## 1.1 Context

At Mercado Bitcoin, users engage in crypto trading via the trading API, mobile app, and website. The trading engine processes millions of operations, matching buy and sell orders. Two types of end users exist: market makers, contributing to the order book depth, and retail users engaging in non-automatic trading. Despite user type, opposing orders result in matches by day's end. Presently lacking a fraud detection mechanism for price manipulation, all orders, regardless of authenticity, enter the order book.

From a retail perspective, this aligns with the expected behavior, as the exchange derives revenue from individual order taxes. However, the market's anonymous, decentralized, and unregulated nature makes it susceptible to manipulation. To address this, we analyze public trading data from Mercado Bitcoin API for anomalies and suspicious activities, focusing on order book data (buy and sell with price and volume) and trade data (historical transactions). Initially exploring Bitcoin historical data from 2013 onwards, we plan to extend our analysis to other cryptocurrencies if inconsistencies emerge in Bitcoin data during the research.

## 1.2 Problem

Financial frauds are not unique to the stock market, cryptocurrency and the Bitcoin ecosystem can be victims of such manipulation. These scams have been extensively researched in traditional stock markets, but there is a lack of deeper and more scientific research on their prevalence and impact in the cryptocurrency space. Such scams pose a significant threat to cryptocurrency exchanges as they can manipulate prices, resulting in potential revenue losses and damage to credibility. Due to the complex nature of these frauds, advanced Artificial Intelligence Models can be applied to detect and prevent them [3, 4].

Although these scams have been extensively researched in traditional stock markets, there is a lack of literature about the use of ML techniques to detect and prevent them on cryptocurrency markets. Therefore, our initial goal is to analyze the public trading data from Mercado Bitcoin using different Machine Learning techniques to, first, investigate if there is indication of fraud on the trading data, and second the type of anomalies. Moreover, if these anomalies are know and if we can compare them to the stock market and other financial domains [5].

## 1.3 Aims and Objectives

***Aim Statement:*** *Crypto scams have cost people more than $1 billion since 2021, according to U.S. Federal Trade Comission. On top of that, there is very little monitoring of manipulative trading. This project seeks to examine the trading data of criptocurrencies on Mercado Bitcoin cryptocurrency exchange, to detect anomalies and what kind of anomalies they are, according to other researches on the stock market. The research will use Artificial Intelligence techniques to conclude either or not the Bitcoin market can be target to such scams.*

***Research Question:*** *Given a dataset composed of trading data on a cryptocurrency exchange, can we determine if there is anomalies on the data and classify them?*

**Objectives**

- Collect trading data from Mercado Bitcoin public api;
- Prepare and transform the collected data;
- Apply fine-tuning techniques on already pre-trained artificial intelligence models;
- Train a variaty of machine learning, deep learning and large language models;
- Evaluate these models by deliberate inserting fraudulent data and check either or not the model will detect those manipulations;
- Compare the results against well know and established models;
- Collect and debate the results.

## 1.4 Justification

According to data from Mercado Bitcoin, the platform has facilitated a total trading volume of 50 billion reais since its inception in 2013, with 200 assets and 3.8 million clients actively trading on the platform. Bitcoin represents 40% of the $1 trillion in crypto assets outstanding. Although is not possible to measure the exact amount of volume target of scams, fraud or even market manipulation is imperative to have a mechanism to identify these anomalies.

Without a proper mechanism to identify or even prevent such fraudulent actions, can deteriorate public trust into the exchange leading to loss on revenue and market share. On the legal side, the cryptocurrency exchange can be prosecuted by traders, companies and other individuals trading on the platform. This also applies to Goverment and authorities. Futhermore, the inaction toward these anomalies can hold back the cryptocurrency economy, preventing new features and the development of the web3 economy itself.

While these concerns are not unique to cryptocurrency exchanges, it is imperative to have means to detect and prevent fraudulent actions in any exchange, including those involving stocks and other traditional financial assets. Despite the importance of this matter, the current measures to detect and stop such actions are often rudimentary and limited, with nonexistent or insufficient regulation being a common obstacle.

All this effort could benefit brazilian authorities, specially *Comissão de Valores Mobiliários* (CVM), *Banco Central do Brasil* (BACEN). Finally the recently passed project on the regulation of cryptocurrency assets by the *Câmara dos Deputados* PL 4401/2021, which brings more regulation to the sector.

# Chapter 2

# Definitions of Terms

## 2.1 Money is Corruptible

Bitcoin (BTC) emerged on the scene in late 2008, allegedly as a response to the financial crisis of 2007-2008, and some have suggested that it was also motivated by frustrations with the bureaucratic nature of the Japanese banking system. However, the latter claim ventures into more conspiratorial territory; although there is no concrete evidence to support this claim, the original author or authors of the Bitcoin whitepaper may have had connections to Japan [6]. Nevertheless, prior to delving into the intricacies of Bitcoin, it is crucial to first explore the concept of money and, more significantly, its foundational aspect: value. In the following sections, we will focus on the economic concept of money as a store of value and medium of exchange and explore how Bitcoin fits into this framework.

What is Money? Or rather, what does money represent?

### 2.1.1 What is Money

If we asked: *What is man's greatest invention?* What would your answer be? There are a lot of options. Would it be fire? Because it gives us warmth, protection, and the ability to cook our meals? Or perhaps you would pick the wheel? Because it's the driving force being the beginnings of trade, commerce, and travel. While both of those are excellent choices, most of the time when we think about the greatest inventions of mankind, we tend to forget one of the most important ones of all: money. Unlike tangible inventions such as fire and the wheel, money, possesses an immaterial nature. It exists as a conceptual construct, lacking inherent value, and its significance is derived solely from the subjective importance we attribute to it. This intangible nature of money often distinguishes it from other notable inventions in the collective human consciousness [7].

Notwithstanding the illusory nature of money, its significance remains unaffected. Before to the establishment of monetary systems, human societies engaged in the direct exchange of goods and services, known as the Barter system. In this system, individuals traded commodities without an assigned intrinsic value, relying solely on subjective evaluations of desired items. Consequently, each transaction was contingent upon the willingness of the parties involved to forfeit possessions in pursuit of their desired commodities. Such an exchange mechanism resembled a game-like scenario [8]. If I desired vegetables for my meal but my only possession was cattle, I would be obliged to offer one of my animals in exchange for bags of vegetables. Similarly, if I required footwear but specialized in tent production, I would have to surrender an entire tent to obtain a pair of slippers. This barter-based system reveals a prominent issue known as asymmetry. As a tent-maker, the exchange of an entire dwelling for simple footwear would undoubtedly leave me feeling disadvantaged. The absence of a standardized medium of exchange presented significant challenges for facilitating agreements between individuals with disparate needs. Moreover, the reliance on a fortuitous occurrence of complementary wants, wherein two individuals simultaneously sought reciprocal possession, further complicated matters, rendering the process inefficient [9].

Our monetary system serves not only as a medium of exchange but also as a store of value. However, prior to the advent of money, certain individuals were unable to effectively preserve their wealth, through no fault of their own. Consider the scenario of a farmer selling tomatoes and a tent maker. The tent maker has the ability to amass a substantial portfolio of real estate in the form of tents, which can be bartered year-round with individuals in need of shelter. Consequently, the tent maker has the opportunity to accumulate wealth. In contrast, the farmer selling tomatoes can only engage in barter transactions during the tomato season. Moreover, due to the perishable nature of tomatoes, long-term storage is not feasible. Thus, despite exerting comparable efforts in their respective businesses, the farmer had no viable means to sustain wealth throughout the year [10]. There's also the problem of having something that only a very few people want. Nowadays, when starting a business, you're often told to find a niche. A small group of people who are very interested in what you have to offer. Before money was a thing, that advice would have left you with nothing worth bartering.

In societies where possessions in high demand, such as weapons, animal skins, and salt, held significant value, individuals who possessed such commodities acquired substantial wealth. The awareness that these items were universally sought-after prompted individuals to engage in anticipatory buying, even if immediate need was absent, to secure future trading opportunities. As a consequence, the emergence of commodity money ensued, whereby goods and services were exchanged for commonly recognized items such as salt or weapons, facilitating subsequent transactions with other parties [11].

Humanity progressed beyond direct barter, encompassing a diverse range of commodities including salt, weapons, and minutecollectibles like shells and beads. This evolution introduced a more efficient method of trade and exchange. Rather than directly swapping goods and services, individuals adopted the practice of using arbitrary objects as intermediary placeholders of value, effectively functioning as IOUs (I Owe You). Subsequently, these placeholders could be utilized to acquire desired goods and services from others. This concept proved remarkably ingenious, ultimately leading to a global transition from the Barter system to the monetary exchange system [12]. However, there has been a persistent limitation associated with this form of exchange. In order for currency to exhibit intrinsic value, it requires a degree of scarcity [7, 13]. The more easily accessible an item is, the lower its perceived worth [14]. When an item is readily obtainable by anyone, its value diminishes considerably. As a result, substances such as sand or shells, which can be effortlessly collected from any beach, do not effectively function as indicators of value [15, 16].

In approximately 770 BC, China witnessed the emergence of the earliest metal coins, marking a significant milestone in the evolution of currency. As a tribute to their historical currency systems, the Chinese craftsmen ingeniously crafted miniature replicas of tools that were previously utilized as forms of exchange. To ensure convenient handling, the coins were deliberately designed in a circular shape, allowing easy retrieval from pockets without causing any discomfort to the fingers. These coins were predominantly cast using bronze, thereby bestowing intrinsic value upon them. This transition marked a pivotal moment in history, as money transformed from a mere symbol to a tangible entity of worth. The scarcity of bronze, a resource not readily available on any beach, further amplified the significance of these coins [17, 18]. During this period, the concept of money had not yet deviated from material reality. The valuation of a coin corresponded directly to the intrinsic value of the metal constituting the coin. For instance, a coin crafted from 1 gram of gold possessed an equivalent worth of precisely 1 gram of gold. This quantifiable attribute allowed for straightforward verification through direct measurement, enabling individuals to visually ascertain that the coin indeed comprised 1 gram of gold.

The realization of the potential power of money was swift among Kings and Rulers [19]. This understanding led to the creation of the first official money mint by Alyattes, the King of Lydia, around 600 BC. These coins were minted from a blend of silver and gold, with each coin featuring a distinctive image serving as a denomination. Consequently, individuals could effortlessly determine the value of their metal possession by observing the pictorial representation on the coin's surface [20]. The pursuit of greater wealth among Kings led to the devaluation of coins through the reduction of precious metal content and the inclusion of cheaper metals [21]. This resulted in the divergence between the face value and actual worth of circulating coins, establishing the illusion of money. The value of coins became divorced from the intrinsic value of their metal composition, relying instead on the dictates of rulers and financial institutions [22]. As an example, the British Pound Sterling ceased to represent a fixed quantity of Sterling Silver and instead denoted a unit of currency determined by authoritative decree.

The emergence of international trade exposed the impracticality of metal coins, leading to the introduction of IOU certificates by the Kings to facilitate long-distance transactions [23]. These certificates, bearing the King's stamp, gained trust and were believed to hold value, as they were expected to be exchangeable for equivalent coins. Initially, this belief corresponded to reality. With the proliferation of IOU certificates in circulation, the necessity for physical coins diminished. Ultimately, the value of the certificates became divorced from their direct convertibility into gold and silver coins. Instead, their value relied on collective trust and shared belief [24]. This shift allowed the paper certificates to retain value based on our perception, even in the absence of an immediate exchange for tangible precious metals.

### 2.1.2 The Illusion of Money

From Ancient Kings to modern-day governments and Central Banks, money has remained an illusion. A mere representation of whose value is determined by the importance people place on it.

The ten thousand Singapore Dollars banknote, while no longer in production, remains the highest denomination in circulation [25]. Despite its intrinsic production cost of fewer than 20 cents, the value of this paper note is upheld by the illusion perpetuated by the fiat currency system [26]. Presently, its monetary equivalence to seven thousand three hundred and forty-five US Dollars enables its utilization in acquiring substantial assets such as houses, cars, and even valuable commodities like gold.

"Fiat" is the fancy word we use to describe the modern-day illusion. It's a Latin word that translates to "let it be done." It's a decree by the government that, in the case of money, determines what its value is and enforces it as legal tender [27, 28].

The elusive nature of money often evades careful consideration, yet akin to historical rulers, contemporary governments possess an understanding of the influential power of currency and persistently strive for its accumulation. Recognizing that the possession of greater quantities of these paper instruments equates to amplified authority, governments adopt the approach of generating additional currency ex nihilo. For instance, in the scenario where the United States government necessitates $340 million dollars to procure an F-22 jet, it possesses the capacity to create the required funds through the act of monetary printing [23, 29]. But there is one problem with this: **inflation**.

The fundamental attribute of money lies in its role as a medium of exchange, conferring value upon it [29]. Consequently, the quantity of money in circulation should align with the aggregate production of goods and services. Should the issuance of money exceeds the availability of goods and services, with all else remaining constant, the resultant effect is an escalation in prices and a subsequent devaluation of the currency itself. This concern resonates with economists and the general population, including individuals such as ourselves, [30], particularly in the context of the current global reserve currency, the United States Dollar.

The year 2020 proved to be an exceedingly challenging period for the world at large, as the onset of the pandemic necessitated the temporary closure of numerous economies, resulting in a considerable reduction in the availability of goods and services and a marked decline in overall economic output, as outlined in the World Economic Outlook report by the International Monetary Fund [31]. To avert economic collapse and the potential disintegration of societal systems, the US government embarked on an unprecedented scale of monetary expansion, surpassing any previous instances of currency printing in its history [32]. As of 2021, the current state of affairs reveals a considerable expansion of the US dollar supply, with approximately 40% of the existing currency having been printed within the last 18 months [33]. This substantial increase in the money supply with the country's output has raised concerns regarding the potential for significant price inflation [34]. Observable evidence of this trend is already apparent in the substantial rise in commodity prices, such as the tripling of lumber prices compared to a year ago. Additionally, discernible price increases can be observed in everyday experiences, including slight increments in prices at favorite restaurants, such as a modest 20-cent rise in the cost of guacamole at Chipotle [35]. Although the provision of stimulus and unemployment checks by governments to their citizens may initially appear beneficial, it entails a double-edged sword. While it undoubtedly assists individuals in dire economic circumstances, it also introduces challenges. Presently, the combined factors of inflationary pressures and an economic slowdown have created difficulties for individuals seeking suitable employment opportunities, not solely due to a lack of willingness but also because certain job options may be less desirable than available alternatives [36, 37].

An illustrative example can be observed in the United States, where the law does not mandate a minimum wage for individuals working as waiters or waitresses [38]. Consequently, some employees in these roles receive meager hourly wages, such as \$2 to \$3, with tips constituting a substantial portion of their earnings. However, due to the implementation of various restrictions and regulations nationwide, coupled with a decrease in customer traffic, there has been a reduction in both customer volume and disposable income, thereby leading to a decline in tip revenue [39]. Inadequate income for employees may result in higher turnover rates as financial needs are not being met. This situation poses a significant risk to businesses, as the lack of a sufficient workforce can ultimately lead to business closure, setting in motion a cascading effect [40]. A valid concern arises regarding the motivation to actively seek employment when the potential income from unemployment and stimulus checks surpasses that from being employed. This circumstance prompts an examination of the available options. Notably, the Federal Reserve of the United States employs a strategic approach to injecting funds into the economy, a process that may not be widely acknowledged, thus stimulating economic activity without substantial public scrutiny [41]. Consequently, the relative attractiveness of alternative income sources may influence individual's decision-making regarding employment prospects [42].

The United States had accumulated a staggering national debt of $29 trillion before 2020, an astounding and challenging figure to comprehend [43]. This debt is primarily financed through the issuance of bonds and Treasury notes, which are essentially contractual instruments offering repayment of a predetermined principal sum alongside interest [44]. Presently, investing in a 10-year U.S. Treasury bond would yield a modest return of 1.23% upon maturity. Therefore, investing $1,000 today would result in a nominal return of a mere $12.30 by 2031. However, this return fails to keep pace with the targeted inflation rate, projected to be around 2% annually [45]. It should be noted that actual inflation rates may surpass the target, although that discussion is beyond the scope of the current context. Consequently, investing in government notes issued by one's own country, whose currency is utilized in daily transactions, leads to a gradual erosion of purchasing power over a decade. Irrespective of these concerns, financial institutions, businesses, and individuals worldwide participate in the acquisition of bonds and treasury notes, thereby providing governments with discretionary funds for utilization [44]. However, when the government confronts the need to fulfill its debt obligations, the previously obtained funds have been fully expended. Consequently, the government initiates repurchases of treasuries and bonds, confining such transactions to prominent financial institutions and remunerating them through freshly created money, effectively conjured from nothingness. The Federal Reserve, for instance, has repurchased over $1 trillion in bonds since March 2020, with plans to persist in such actions well into the future [46].

Through government injections, banks are empowered to expand their lending activities, thereby increasing interest income and fostering economic growth [46]. However, this surge in lending simultaneously expands the aggregate money supply, leading to a depreciation in the value of each dollar. The implementation of multi-trillion dollar stimulus payments and infrastructure packages raises questions regarding the sustainability of such practices. The influx of new money results in a devaluation of existing money, whereby the balance in an individual's bank account remains unchanged, yet its purchasing power diminishes owing to the influx of newly minted money [47]. Consequently, the retention of wealth in a fiat currency like the US dollar progressively erodes its value, ultimately impeding the ability to acquire goods and services despite nominal bank balances.

The reality that money is nothing but an illusion is one that we must all embrace. Only then will the path to financial freedom become clearer. Understanding that money does not have any intrinsic value in itself but instead only inherits the value we give it.

As the money supply continues to expand, the purchasing power of each dollar held in one's possession inevitably erodes, whereas the dollar-denominated value of global assets tends to appreciate [48]. Nevertheless, this perceived growth can be likened to an optical illusion, employing deceptive mechanisms. Despite the seemingly unrelenting ascent of the stock market, the underlying reality is far from reassuring. The relentless depreciation of the currency compounds the situation, eroding its value daily. For example, if the Dow Jones Industrial Average, which serves as a benchmark for the performance of 30 major US companies, were denominated in terms of gold rather than USD, it would become apparent that its value has essentially stagnated since 1997 [49].

But what's the end goal of all of this? With fiat and an unlimited supply of money, will the value of each currency just continue to decrease until the end of time? Will the gap between the rich and the poor continue to grow wider? Or are we going to finally fix a problem as old as man itself and stop placing our financial success in the hands of those who are destroying it day by day? Money is corruptible.

Only time will tell, but just to know, there is a way out: **Bitcoin**.

## 2.2 Market Manipulation

The medium of exchange is a widely accepted instrument or asset that serves as a common intermediary for transactions, facilitating the exchange of goods and services [50]. It functions as a standardized unit of account, allowing the valuation and comparison of different goods and services. The medium of exchange eliminates the need for barter and enables efficient value transfer in economic transactions [51]. Manipulation of the medium of exchange refers to deliberate actions taken to influence or distort its value, availability, or circulation in order to gain an unfair advantage or control over economic transactions. This manipulation can occur through various means and can have significant implications for market participants and overall economic stability.

Additionally, manipulation can occur through market interventions, such as insider trading, price manipulation, or spreading false information to manipulate the perception of value or demand for certain assets or currencies. These actions can distort market prices, disrupt fair competition, and create opportunities for manipulation by individuals or institutions with privileged information or significant market power. One way to study the manipulation of the medium of exchange is through the lens of economics. In this case, the focus would be on understanding how market forces and government policies affect the supply and demand for different types of currency and other forms of payment. For example, a country's central bank may adjust interest rates or change monetary policy in order to influence the value of its currency relative to others. Similarly, the government may regulate financial markets or institute taxes on certain transactions in order to discourage their use [52].

In the following sections, we will delve into the various forms of market manipulation a medium of exchahge can be target of.

### 2.2.1 Crypto Market Manipulation

Crypto market manipulation should be differentiated from currency manipulation, which is primarily carried out by governments and authorized entities like central banks [53]. Currency manipulation, though legal, may face challenges from other countries. Governments may engage in currency devaluation to enhance their competitiveness [53].

Cryptocurrency manipulation encompasses a range of deceptive practices aimed at influencing the cryptocurrency market for personal gain or to create artificial market conditions. While it is challenging to provide an exhaustive list, some well-known forms of cryptocurrency manipulation include:

#### Pump and Dump

Pump-and-dump fraud is a manipulative practice commonly observed in cryptocurrency markets. It involves artificially inflating the price of a cryptocurrency through coordinated efforts, creating a buying frenzy among unsuspecting investors. Once the price reaches a peak, the fraudsters sell their holdings at the inflated price, causing the price to plummet. This results in significant losses for those who bought the cryptocurrency during the manipulation [54].

Pump-and-dump schemes typically follow a similar pattern [55]:

1. *Accumulation Phase:* The fraudsters accumulate a significant amount of the targeted cryptocurrency at relatively low prices, often in low-liquidity markets.

2. Promotion Phase: Using various means such as social media, online forums, or messaging platforms, the fraudsters create a buzz around the targeted cryptocurrency. They disseminate positive news, rumors, or false information to attract potential investors.

3. *Pump Phase:* As the promotion gains traction, the fraudsters initiate a buying spree, often in a coordinated fashion. This influx of demand drives up the price of cryptocurrency rapidly.

4. *Dump Phase:* Once the price reaches a peak and enough retail investors have entered the market, the fraudsters sell their holdings, flooding the market with cryptocurrency. This sudden increase in supply causes the price to collapse, leaving unsuspecting investors with losses.

5. Pump-and-dump fraud exploits the lack of regulatory oversight and the relatively small market capitalization of certain cryptocurrencies. It takes advantage of investors fear of missing out (FOMO) and their susceptibility to market manipulation techniques.

Researchers and regulators have extensively studied pump-and-dump fraud in cryptocurrency markets, aiming to understand its characteristics, impact, and potential detection methods. However, the decentralized and anonymous nature of cryptocurrencies poses challenges in effectively combating this form of manipulation [56, 57].

### Wash Trading

Wash trading is a fraudulent practice commonly observed in cryptocurrency markets. It involves creating artificial trading activity by buying and selling the same cryptocurrency simultaneously or in quick succession, with the intention of misleading other market participants. The primary goal of wash trading is to create a false impression of high trading volume and liquidity, which can attract investors and manipulate the market price [58].

In a wash trading scenario, a single entity or a group of colluding entities control both sides of the trade, effectively trading with themselves. This activity creates the illusion of market demand and activity, making the cryptocurrency appear more popular and active than it is. By artificially inflating the trading volume, the fraudsters aim to attract other traders and investors to participate in the market. Wash trading can occur through various methods, such as executing trades through multiple accounts controlled by the same entity, using automated trading bots to simulate trading activity, or coordinating with other individuals or entities to perform simultaneous buy and sell orders. The goal is to manipulate market sentiment, create a false sense of market depth, and potentially influence the price of the cryptocurrency [59].

Wash trading is considered illegal in regulated financial markets as it undermines market integrity and misleads investors. However, in the cryptocurrency market, which often operates with limited regulations and oversight, wash trading remains prevalent. Detecting and combating wash trading can be challenging due to the lack of transparency and the pseudonymous nature of cryptocurrency transactions. Researchers and market surveillance teams are actively exploring data analysis techniques and algorithms to identify patterns indicative of wash trading and develop effective countermeasures [58, 59].

### Front-running

front-running is a fraudulent practice that can occur in cryptocurrency markets, where a trader or entity exploits non-public information to gain an unfair advantage over other market participants. It involves executing trades based on advanced knowledge of pending orders or transactions that are likely to impact the market price [60].

In the context of cryptocurrency, front-running typically involves a trader or entity having access to privileged information about a large buy or sell order that is about to be executed. The front runner quickly enters their order ahead of the known trade, taking advantage of the subsequent price movement resulting from the anticipated transaction. By front-running, the fraudulent party can potentially profit from the price impact caused by the forthcoming order. This practice is unethical and can harm market integrity by exploiting information asymmetry and disadvantaging other traders who do not possess the same privileged knowledge. It can erode trust in the market and deter fair participation. Detecting and preventing front-running in cryptocurrency markets can be challenging due to the decentralized and pseudonymous nature of the transactions. However, regulatory bodies and market surveillance teams are exploring methods to identify suspicious trading patterns and investigate potential instances of front-running [61].

### Insider Trading

Insider trading fraud in the cryptocurrency market involves individuals or entities trading based on non-public information that can potentially influence the market price of a cryptocurrency. It refers to the act of buying or selling cryptocurrencies using confidential information not yet available to the general public, thereby gaining an unfair advantage over other market participants.

Insider trading can occur in various forms within the cryptocurrency market. It may involve individuals with access to privileged information about upcoming announcements, partnerships, regulatory decisions, or other market-moving events. By trading on this information before it becomes public knowledge, insiders can profit from the subsequent price movement.

Engaging in insider trading is considered fraudulent and illegal in many jurisdictions, as it undermines the principles of fairness, transparency, and equal opportunity in financial markets. It can harm market integrity, erode investor confidence, and distort the true market value of cryptocurrencies. Detecting and preventing insider trading in the cryptocurrency market can be challenging due to the pseudonymous nature of transactions and the global and decentralized nature of the market. However, regulatory authorities and exchanges are implementing measures such as enhanced surveillance systems, strict disclosure requirements, and cooperation with law enforcement agencies to deter and identify instances of insider trading [62, 63].

#### False News and Rumors

False news and rumors fraud in the cryptocurrency market refer to the dissemination of misleading or fabricated information to manipulate cryptocurrency prices for personal gain. It involves spreading false news, exaggerated claims, or unfounded rumors about cryptocurrencies, projects, or market events to deceive investors and create artificial price movements. Perpetrators of false news and rumors fraud may use various methods to spread misinformation. They can utilize social media platforms, online forums, news, and websites, or even create fake accounts to amplify the reach of their fraudulent claims. The false information may include announcements of partnerships, regulatory approvals, technological breakthroughs, or negative news targeting specific cryptocurrencies or projects.

False news and rumors aim to create a sense of urgency or FOMO (fear of missing out) among investors, leading them to make impulsive investment decisions based on inaccurate or incomplete information. By manipulating market sentiment, fraudsters can artificially inflate or deflate the price of a cryptocurrency, allowing them to profit from the subsequent price movement.

Detecting and combating false news and rumors fraud in the cryptocurrency market is challenging due to the decentralized nature of information dissemination and the lack of regulatory oversight. However, industry participants, regulatory bodies, and exchanges are increasingly implementing measures to combat this type of fraud. These include improved due diligence on information sources, community-driven fact-checking initiatives, and stricter regulations on the disclosure of news and information [64, 65].

### 2.2.2 What Are Spoofing and Layering?

Spoofing is a trading practice that lacks a universally accepted definition, but certain behaviors are commonly recognized as constituting spoofing. A typical spoofing scheme involves a trader placing a substantial order on one side of the to cancel it before execution, while simultaneously entering one or more smaller orders on the opposite side that the trader intends to execute. By placing the large order, the trader creates an illusion of market depth, prompting responses from other market participants that ultimately benefit the trader's smaller positions. These responses occur because many participants shape their market strategies based on their perceptions of supply and demand at different price levels. Often, these responses are automated and occur nearly simultaneously due to the widespread use of trading algorithms [66, 67].

Spoofing and layering are typically not isolated incidents but rather ongoing practices that span over extended periods, involving the placement of numerous spoof or layered orders. For instance, in August 2019, a former J.P. Morgan Chase precious metals trader admitted to engaging in thousands of instances of spoofing between 2007 and 2016. Furthermore, a 2018 enforcement action by the CFTC revealed over 36,000 instances of spoof orders, while an earlier enforcement action by the SEC uncovered more than 325,000 layered transactions, corresponding to the entry of over eight million layered orders [68, 69].

The repercussions of spoofing can lead to significant losses for the affected traders. For instance, in an October 2018 case where codefendants pleaded guilty, market participants trading futures contracts in the spoofed markets suffered losses exceeding $60 million, as estimated by the DoJ. Additionally, in a separate spoofing case settled by Merrill Lynch Commodities, Inc. in June 2019 with the CFTC and the DOJ, the settlement encompassed disgorgement and restitution. The NPA entered into by Merrill Lynch with the DOJ highlighted the detrimental impacts of the spoofing scheme, including exposing market participants to potential losses, unwinding precious metals futures positions at a financial detriment, incurring investigative and litigation costs, and causing reputational damage [70, 71].

Layering represents a more advanced iteration of spoofing techniques. In a typical layering scheme, multiple limit orders are strategically placed on one side of the market at various price levels, without the intention of execution. The primary objective remains the creation of an illusionary shift in supply and demand levels, thereby artificially influencing the price of the targeted commodity or security. Subsequently, an order is executed on the opposite side of the market at the artificially induced price, while the previously entered multiple orders are swiftly canceled. The foundations of spoofing and layering rely on the fundamental microeconomic principle that an increase in supply exerts downward pressure on prices, while an increase in demand drives prices upward. Nevertheless, trading techniques have evolved and grown more intricate in recent years. Noteworthy variations include spoofing with vacuuming, collapsing of layers, flipping, and the spread squeeze. Moreover, cross-market schemes executed across highly correlated markets introduce further complexities. The heightened complexity has significantly exacerbated

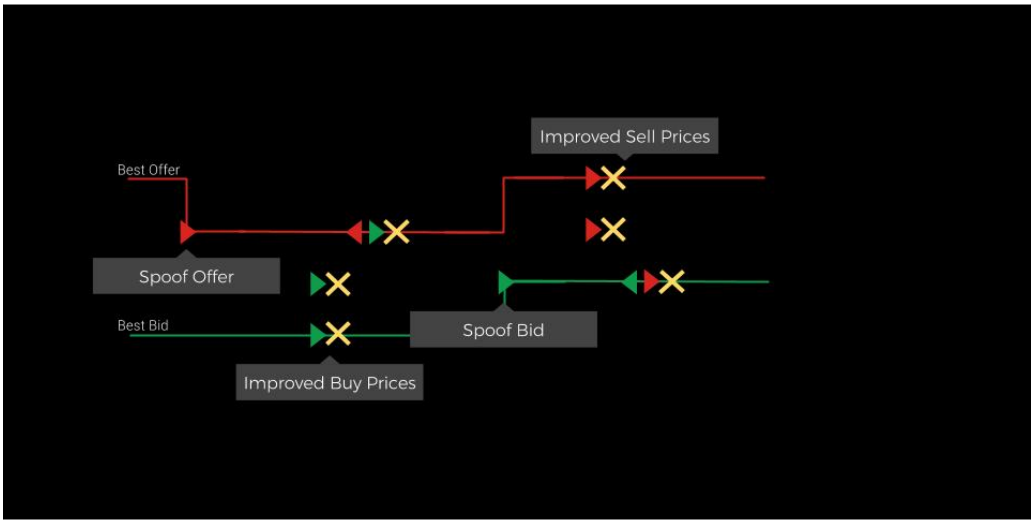


Figure 2.1: A Tipical Spoofing (Reference: [72]).

the challenge of detection [73, 74].

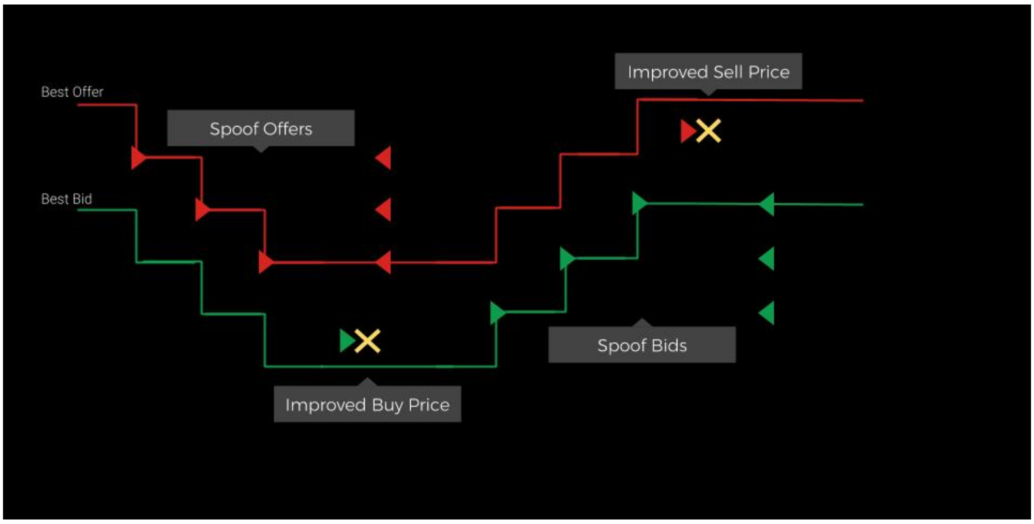


Figure 2.2: A Tipical Layering (Reference: [75]).

The motivations of a trader in a spoofing or layering scheme typically revolve around market manipulation for financial gain, although this is not always the case.

Another motivation involves testing the market's response to specific order types. A notable example occurred in September 2018 when Mizuho Bank settled allegations of engaging in multiple acts of spoofing on the Chicago Mercantile Exchange (CME) and Chicago Board of Trade (CBOT), the world's largest futures exchange. Mizuho's trader was accused by the U.S. CFTC of placing spoof orders to assess mar ket reaction to their trading activities, as part of their anticipation of hedging Mizuho's swaps positions with futures contracts at a later date. It is important to note that the CFTC did not claim that the trader executed or placed genuine orders that directly benefited from the spoofed large orders. In previous spoofing cases handled by the CFTC, both spoof and genuine orders were alleged to be involved in the misconduct. However, the CFTC maintains that a trader's conduct is considered unlawful regardless of whether the motive is market manipulation or assessing market reactions. While this position has not been tested in court, the CFTC's stance is expected to be upheld given that the Commodity Exchange Act (CEA) does not specify any motive requirement for prohibited spoofing. [76, 77, 78].

In January 2018, the U.S. CFTC announced the establishment of a Spoofing Task Force, representing a collaborative effort within the CFTC's Division of Enforcement, with team members stationed across various CFTC offices in Chicago, Kansas City, New York, and Washington, D.C. The purpose of the Task Force, as stated by the CFTC, was to "eradicate spoofing from our markets." Concurrently, the CFTC disclosed the resolution of spoofing enforcement actions involving Deutsche Bank, UBS, and HSBC, resulting in fines reaching up to $30 million. Furthermore, civil complaints alleging spoofing and manipulation were filed against six individuals and one company in coordination with the U.S. DOJ and the Federal Bureau of Investigation (FBI). The DOJ also pursued criminal charges against these individuals, as well as two others. This series of actions marked the largest coordinated enforcement effort involving criminal authorities in the history of the CFTC and was identified by the DOJ as its most extensive criminal enforcement action in the futures market to date. Subsequently, a review conducted in September 2018 concluded that the CFTC's dedication to combating spoofing remained steadfast and ongoing. By the end of the fiscal year on September 30, 2018, the CFTC's Division of Enforcement had initiated a higher number of actions related to spoofing and manipulation than in any prior year. While the CFTC averaged six such cases per year between 2009 and 2017, it filed 26 cases in 2018. More recently, in August 2019, a comprehensive evaluation affirmed that spoofing continues to be a prominent area of focus for both the DOJ and the CFTC [79, 80].

### 2.2.3 Spoofing and Layering on Bitcoin Trading

In the context of the Bitcoin market, spoofing remains a concern. Although the legality of spoofing in the cryptocurrency domain is still evolving, engaging in spoofing practices is generally discouraged and potentially illegal in many jurisdictions. Traders attempting to manipulate the Bitcoin market through spoofing may face regulatory consequences, similar to the case of a California day trader who was penalized by the SEC for a spoofing scheme.

The impact of spoofing on the Bitcoin market is a topic of debate. Some argue that spoofing can artificially affect short-term price movements, causing panic selling or buying among leveraged traders. However, long-term investors, commonly referred to as hodlers, are less likely to be significantly affected by short-term market manipulations. They focus on the fundamental factors driving Bitcoin's value, such as increasing adoption and scarcity.

Bitcoin market dynamics differ from traditional financial markets due to its decentralized nature and limited supply. The presence of spoofing, while acknowledged, is considered less critical in the long-term valuation of Bitcoin. Hodlers, who accumulate and hold Bitcoin for extended periods, recognizing instances of spoofing can serve as confirmation for the continuation of price movements in a specific direction. One might proceed to analyze a real order book example, specifically Bitcoin to the dollar, wherein buying Bitcoin is priced at $4,200 and selling it is valued at $4,190. Notably, there are 77 Bitcoin available for purchase at $4,200 and 30 Bitcoin was available at $4,190. The "asks" represent the selling offers, denoted in red, while the "bids" reflect the buying bids, depicted as green (represented by yellow in the absence of an alternative color). If a significant amount of selling offers (red) and a limited number of buying bids (green) are observed, it indicates substantial selling pressure, implying a potential downward price movement.

Conversely, if there is a considerable number of buying bids (green), it suggests a potential upward price movement. This analysis is based on the assumption that to drive the price up, the existing sell offers must be gradually consumed. Consequently, if a surplus of sell offers exists (red), it indicates a substantial "ask wall." Conversely, a large number of buy bids (green) represents a significant "bid wall," implying a potential price increase. Returning to the presentation, a scenario is presented where 450 coins are available at a price of $10 and 150 coins are available at $9. In this case, assuming the market has been declining, the individual intends to sell their coins at the highest possible price, ideally $10, without placing an actual trade.

To manipulate the market without executing a trade, the individual places a deceptive buy wall, known as spoofing. This is achieved by placing a series of orders at $8 and $7, thereby inflating the apparent volume available at these levels. However, the individual has no intention of buying coins at these levels. By creating a facade of significant buying interest, the market is deceived into perceiving the end of the downturn, resulting in increased buying activity. Consequently, the price rises and the individual cancels their deceptive orders. Capitalizing on the price movement, the individual sell their coins at the inflated price, reducing their losses compared to selling at the initial lower price.

Subsequently, the market may resume its downward trajectory. To detect spoofing, attention must be paid to the order book, where a sudden influx of orders at a particular price level, accompanied by a low number of orders, can indicate either genuine large-scale trading activity or the presence of spoofing. Similarly, an abnormally high volume at a particular price level may indicate either substantial buying interest or spoofing.

This analysis should be contextualized within the price movement, considering factors such as volume trends and market conditions. Traders can potentially profit from spoofing by observing the initial price movement triggered by the spoofer, anticipating the subsequent continuation of the price trend, and executing appropriate trading strategies, such as short-selling or buying.

# Chapter 3

# Methodology

## 3.1 Design Science Research Process

The Design Science Research process consists of a series of iterative steps that guide the creation, validation, and application of the designed artifact. The steps include problem identification and motivation, definition of objectives, design and development, demonstration and evaluation, and communication of results [81, 82]. In this study, these steps are adapted to the specific context of building a language model pipeline for detecting anomalies on trading data of cryptocurrencies transactions.

#### Problem Identification and Motivation

The first step of the DSR process involves identifying and defining the problem to be addressed. In the realm of cryptocurrency markets, anomalies are deceptive trading practices that can artificially inflate trading volumes and manipulate market prices [58, 83]. The rapid growth of cryptocurrency markets, including Bitcoin, has highlighted the need for effective tools to detect and prevent such manipulative activities [84]. Therefore, the problem addressed in this study is the detection of anomalies on cryptocurrencies trading, using advanced language model techniques.

#### Objectives

The objectives of this methodology are as follows:

1. To design a language model pipeline capable of analyzing Bitcoin time series data and identifying of possible patterns indicative of anomalies.
2. To implement and develop the designed pipeline using state-of-the-art natural language processing (NLP) and machine learning (ML) techniques.

3. To evaluate the performance of the language model pipeline using relevant metrics, such as precision, recall, F1-score, and receiver operating characteristic (ROC) curve analysis.

4. To compare the effectiveness of the developed pipeline with existing methods for anomaly detection in cryptocurrency markets.

**Design and Development**

The design and development phase encompasses the creation of the language model pipeline for detecting anomalies in the cryptocurrencies time series dataset. The pipeline consists of the following components:

1. Data Collection and Preprocessing: Historical Bitcoin trading data, including price, volume, and order book information, will be collected from Mercado Bitcoin public api. The data will be preprocessed to remove noise, normalize features, and create suitable input representations for the language model.

2. Feature Engineering: Relevant features, such as price movement patterns, trading volume fluctuations, and order book imbalances, will be extracted from the preprocessed data. These features will serve as inputs for the language model.

3. Language Model Architecture: A deep neural network-based language model, such as a transformer architecture [85], will be designed to process the extracted features and learn patterns associated with fraudelent activities. Pre-trained models and fine-tuning will be evaluated as well.

4. Training and Fine-Tuning: The language model will be trained using a labeled dataset containing instances of anomalies, as well as genuine trading behaviors. Fine-tuning techniques, such as transfer learning, will be employed to enhance the model's ability to detect manipulative activities [86].

**Demonstration and Evaluation**

The demonstration and evaluation phase assesses the effectiveness of the developed language model pipeline. The following steps will be taken:

1. Simulation and Testing: Simulated anomalies scenarios will be created to test the pipeline's ability to identify manipulative patterns. Additionally, the pipeline will be tested on a holdout dataset to evaluate its real-world performance.

2. Performance Metrics: The pipeline's performance will be evaluated using standard metrics, including precision, recall, F1-score, and ROC curve analysis. These metrics will provide insights into the model's ability to correctly identify anomalies activities.
3. Comparison with Existing Methods: The performance of the language model pipeline will be compared with existing methods for detecting anomalies in cryptocurrency markets. This comparison will highlight the pipeline's innovation and effectiveness.

### Closure

The final phase of the DSR process involves communicating the results of the study. This includes presenting the design and development of the language model pipeline, detailing the evaluation outcomes, and discussing the implications of the findings for detecting anomalies in Bitcoin trading.

Throughout the research process, ethical considerations related to data privacy, potential bias, and unintended consequences of model deployment will be taken into account [87, 88]. Measures will be implemented to ensure the responsible use of technology in detecting manipulative activities.

It is important to acknowledge certain limitations of the proposed methodology, such as the availability and quality of labeled training data, the potential for false positives and false negatives in the detection process, and the generalizability of the language model to evolving trading patterns.

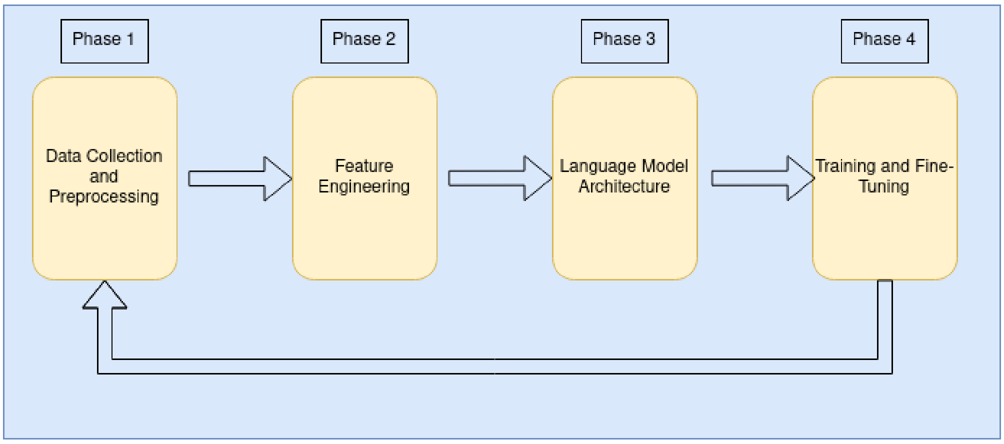


Figure 3.1: Proposed methodology.

## 3.2 Methods

### 3.2.1 Data Collection

We will collect data from the public API provided by Mercado Bitcoin [1] [2]

The first dataset will be created from day-summary endpoint. This endpoint returns daily-summary of trades carried out. Here we plan to collect historical Bitcoin market data, to detect the market behaviour on a given day. As Mercado Bitcoin first started its activities on 2013, we will have data starting at 2013 to nowdays. The main goal is to have some mechanism to forecast the Bitcoin market movement, on which we plan to have some undestand on the behaviour of the market. The table 3.1 describes the data that form this dataset.

Table 3.1: Historical Bitcoin market data, by day.

| Data | Description | Type | Format |
|---|---|---|---|
| date | Date | String | AAAA-MM-DD |
| opening | Opening price (first trade) | Decimal | 262.99999 |
| closing | Closing price (last trade) | Decimal | 269.0 |
| lowest | Lowest price | Decimal | 260.00002 |
| highest | Highest price | Decimal | 269.2 |
| volume | Volume of trading activity (BRL) | Decimal | 7253.1336356785 |
| quantity | Quantity of the pair negotiated | Decimal | 27.11390588 |
| amount | Number of unique tradings | Integer | 28 |
| avg_price | Average Price | Decimal | 267.5060416518087 |

The second dataset candles will be used to determine, on a given moment, if some fraud is ocurring. As Bitcoin is extreme volatile we need a time window information to detect an anomaly. The table 3.2 describes the data that form this dataset.

Table 3.2: Historical Bitcoin market data by a giving period of time (candle)

| Data | Description | Type | Format |
|---|---|---|---|
| c | Closing price | Array of strings | ["500.00000000","1000.00000000"] |
| h | Highest price | Array of strings | ["1000.00000000","1000.00000000"] |
| l | Lowest price | Array of strings | ["500.00000000","300.00000000"] |
| o | Opening price | Array of strings | ["1000.00000000","300.00000000"] |
| t | Bucket start time (UTC) | Array of integers | [1652119200,1652187600] |
| v | Volume of trading activity | Array of strings | ["4.00000000","2.00000000"] |

Dataset 3.2 uses the same data that forms a candle chart [3]

[1] APIV3
[2] APIV4
[3] chart

## 3.3 Schedule

| | 2023 | | | | 2024 | | |
|---|---|---|---|---|---|---|---|
| | Sep | Oct | Nov | Dec | Jan | Feb | Mar |
| Data Collection | ■ | ■ | | | | | |
| Set Up the Model Environment | | ■ | | | | | |
| Fine-Tuning Pre-Trained Models | | ■ | ■ | | | | |
| Result's Discussion | | | | ■ | ■ | | |
| Configure the Training Script | | | | ■ | ■ | | |
| Training the Model | | | | ■ | ■ | ■ | |
| Fine-tuning and Model Optimization | | | | ■ | ■ | ■ | |
| Result's Discussion | | | | ■ | ■ | | |
| Deploy the Trained Model | | | | ■ | ■ | ■ | |
| Thesis Writing | | ■ | ■ | ■ | ■ | ■ | |
| Preparation of Presentation | | | | | | ■ | ■ |

We plan to initiate and finish *Data Collection* within two months, starting in October 2023. In this phase, data from the Mercado Bitcoin public API will be collected to form two datasets: one containing historical data on which we plan to forecast the Bitcoin price, and a second one containing the actual movement price of Bitcoin. With this, we can analyze the market for fraud. More about the dataset is in 3.2.1.

Next, we plan to set up and configure a development environment to conduct our research. Using the cloud powered by artificial intelligence pipelines

Fine-tuning is where we will be testing already-trained models by using our dataset and goals. In this phase, we plan to use models trained for financial tasks such as *BloombergGPT*.

At the end of those phases, we will collect results and debate them, checking if we meet the requirements, e.g., detecting whether or not spoofing and layering happened by deliberately creating fraudulent data on the market.

On Configure the Training Script, we plan to develop an autonomous training mechanism with a variety of models and hyperparameters.

Training the model is where the training script will be applied with a different approach. Using or not labeled data, e.g., telling which movement on the market should be considered a fraud,

Model optimization is where we will deploy the model and maintain it.

The actual writing of the dissertation thesis will take place alongside all the named phases.

## 3.4 Early Conclusions

This dissertation aims to employ machine learning techniques to identify anomalies in the Bitcoin market, which are tactics used by scammers to manipulate Bitcoin prices. We will utilize two datasets, one for market forecasts and the other for real-time Bitcoin prices, obtained from the public endpoint of the Mercado Bitcoin cryptocurrency exchange. Employing the Design Science Research Process, we will develop various machine learning models to detect these fraudulent activities, potentially leading to the creation of an innovative model applicable to other cryptocurrency contexts and anomaly analyses.

The absence of effective mechanisms to identify and prevent such fraudulent actions poses a risk to the exchange's reputation, revenue, and market share. Legal consequences may also arise, as traders, companies, individuals, and government authorities may take legal action against the exchange. Moreover, failing to address these anomalies can hinder the cryptocurrency economy's progress and the development of the broader web3 economy.

# References

[1] Allen, Franklin and Douglas Gale: *Stock-price manipulation*. The Review of Financial Studies, 5(3):503–529, 1992. vi

[2] Allen, Franklin, Lubomir Litov, and Jianping Mei: *Large investors, price manipulation, and limits to arbitrage: An anatomy of market corners*. Review of Finance, 10(4):645–693, 2006. vi

[3] Zhang, Xiaojun, Ying Wen, Jie Zhou, Wei Zhang, and Xiaofeng Liao: *Financial fraud detection in cryptocurrency exchanges: A comprehensive survey*. IEEE Access, 8:193150–193172, 2020. 2

[4] Zainal, Anazida, Joarder Kamruzzaman, and Ruhul A Sarker: *A review on machine learning techniques for the detection of financial statement fraud*. International Journal of Financial Studies, 6(3):70, 2018. 2

[5] Bhattacharyya, Siddhartha, Sanjay Jha, and Kurian Tharakunnel: *A survey of data mining techniques for fraud detection*. ACM Computing Surveys (CSUR), 43(4):26, 2011. 2

[6] Nakamoto, Satoshi: *Bitcoin: A peer-to-peer electronic cash system*. 2008. `https://bitcoin.org/bitcoin.pdf`. 4

[7] Smith, Adam: *The Wealth of Nations: An inquiry into the nature and causes of the Wealth of Nations*. Harriman House Limited, 2010. 4, 6

[8] Durlauf, Steven and Lawrence E Blume: *The new Palgrave dictionary of economics*. Springer, 2016. 5

[9] Goodhart, Charles AE: *The two concepts of money: implications for the analysis of optimal currency areas*. European journal of political economy, 14(3):407–432, 1998. 5

[10] Meneses, Italo Bezerra de: *On the origins of money*. MISES: Interdisciplinary Journal of Philosophy, Law and Economics, 4(2):585–587, 2016. 5

[11] Polanyi, Karl: *Trade and market in the early empires: Economies in history and theory*. 1965. 6

[12] Graeber, David: *Debt: The first 5000 years*. Penguin UK, 2012. 6

[13] Ricardo, David: *On the principles of political economy*. J. Murray London, 1821. 6

[14] Marshall, Alfred: *Principles of economics: unabridged eighth edition.* Cosimo, Inc., 2009. 6

[15] Klein, P.G.: *Principles of Economics.* Ludwig von Mises Institute, 2011, ISBN 9781610162029. `https://books.google.com.br/books?id=GYjEtAEACAAJ`. 6

[16] Hicks, John R: *Theory of employment, interest and money.* The Economic Journal, 46(182):238–253, 1936. 6

[17] Li, Xiuhua: *The formation and spread of the ancient chinese coinage system.* East Asian Archaeology, 3(1):95–106, 2003. 6

[18] Hartill, David: *Cast Chinese Coins.* Trafford Publishing, 2nd edition, 2005. 6

[19] Cribb, Joe: *Money: From Cowrie Shells to Credit Cards.* British Museum Press, 1991. 6

[20] Vries, Ad de: *The Industrial Revolution and the Industrious Revolution.* Cambridge University Press, 2008. 6

[21] Weatherford, Jack: *The History of Money.* Crown Business, 1997. 7

[22] Ferguson, Niall: *The Ascent of Money: A Financial History of the World.* Penguin Books, 2009. 7

[23] Graeber, David: *Debt: The First 5000 Years.* Melville House, 2011. 7, 8

[24] Ingham, Geoffrey: *The nature of money.* Polity, 36(3):387–412, 2004. 7

[25] Goodhart, Charles: *The Two Concepts of Money: Implications for the Analysis of Optimal Currency Areas.* European University Institute, 1998. 7

[26] Gupta, Chirag: *The myth of intrinsic value: The case of fiat money.* Journal of Interdisciplinary Economics, 31(2):177–195, 2019. 7

[27] Reinhart, Carmen M. and Kenneth S. Rogoff: *This Time Is Different: Eight Centuries of Financial Folly.* Princeton University Press, 2018. 7

[28] Friedman, Milton: *The role of government in education.* Economic Affairs, 20(4):4–8, 2000. 7

[29] Mankiw, N. Gregory: *Principles of Macroeconomics.* Cengage Learning, 2014. 8

[30] Blinder, Alan S.: *Quantitative easing: Entrance and exit strategies.* The Economic Journal, 120(519):50–51, 2010. 8

[31] Fund, International Monetary: *World economic outlook, october 2020: A long and difficult ascent.* 2020. 8

[32] Blinder, Alan S.: *The covid-19 crisis: Economic policy implications.* NBER Working Paper Series, w26935, 2020. 8

[33] Federal Reserve System, Board of Governors of the: *Money stock and debt measures h.6 release.* 2023. https://www.federalreserve.gov/releases/h6/current/default.htm. 8

[34] Blanchard, Olivier: *Inflation expectations and uncertainty in the time of covid-19: An overview.* NBER Working Paper Series, w28106, 2021. 8

[35] Labor Statistics, Bureau of: *Consumer price index summary.* 2023. https://www.bls.gov/news.release/cpi.nr0.htm. 8

[36] Office, Congressional Budget: *The macroeconomic effects of the american rescue plan act.* 2020. 8

[37] Kahn, Lisa B. and Bhashkar Mazumder: *Job loss and reservation wages during the covid-19 recession.* Brookings Papers on Economic Activity, 51(1):289–356, 2020. 8

[38] Labor, United States Department of: *Minimum wages for tipped employees.* 2023. https://www.dol.gov/agencies/whd/state/tipped. 8

[39] Labor Statistics, Bureau of: *Occupational employment and wages, may 2022.* 2022. https://www.bls.gov/oes/2022/may/oes356011.htm. 9

[40] Azar, Ariel and Ioana E. Marinescu: *Labor market concentration.* NBER Working Paper Series, w26634, 2020. 9

[41] Federal Reserve System, Board of Governors of the: *The federal reserve system: Purposes and functions.* 2021. https://www.federalreserve.gov/aboutthefed/pf.htm. 9

[42] Office, Congressional Budget: *Policies that would increase economic output and employment in the short term.* 2021. 9

[43] Treasury, U.S. Department of the: *The debt to the penny and who holds it.* 2023. https://www.treasurydirect.gov/NP/debt/current. 9

[44] Treasury, U.S. Department of the: *Treasury securities.* 2023. https://home.treasury.gov/policy-issues/financial-markets-financial-institutions-and-fiscal-service/public-debt. 9

[45] Federal Reserve System, Board of Governors of the: *Monetary policy and inflation.* 2022. https://www.federalreserve.gov/monetarypolicy/inflation.htm. 9

[46] Federal Reserve System, Board of Governors of the: *Statement on longer-run goals and monetary policy strategy.* 2020. https://www.federalreserve.gov/monetarypolicy/review-of-monetary-policy-strategy-tools-and-communications-statement-on-longer-r htm. 9

[47] Lavoie, Michel: *Currency devaluation and domestic output.* Review of Political Economy, 6(3):309–319, 1994. 10

[48] Bernanke, Ben S.: *The global saving glut and the u.s. current account deficit.* Board of Governors of the Federal Reserve System, 2005. `https://www.federalreserve.gov/boarddocs/speeches/2005/200503102/default.htm`. 10

[49] Shiller, Robert J.: *Irrational exuberance.* The Economic Journal, 111(471):652–653, 2001. 10

[50] Mankiw, N. Gregory: *Principles of Macroeconomics.* Cengage Learning, 7th edition, 2014. 10

[51] Friedman, Milton: *Money: M1, m2, and m3.* The Journal of Political Economy, 112(2):S117–S134, 2004. 10

[52] Domanski, Dietrich and Vladyslav Sushko: *Currency manipulation: The imf and wto.* BIS Quarterly Review, September:79–91, 2011. 11

[53] Goldstein, Morris and Nicholas R. Lardy: *Currency manipulation: The imf and wto.* Peterson Institute for International Economics Policy Brief, 2018. `https://www.piie.com/publications/policy-briefs/currency-manipulation-imf-and-wto`. 11

[54] Karim, Mohamed A and Samah Mikhael: *Manipulation detection in cryptocurrency markets.* IEEE Access, 6:11044–11054, 2018. 11

[55] Cheah, Eng Tuck and John Fry: *Pump and dump schemes in cryptocurrency markets.* Social Science Research Network, 2015. 11

[56] Jin, Xinghua, Xiaohua Cheng, Qian Su, and Ting Liu: *Pump-and-dump manipulation in cryptocurrency markets.* Information Systems Frontiers, 22(6):1389–1402, 2020. 12

[57] Yang, Yuxing, Yi Zhang, and Yang Yang: *Pump and dump on the cryptocurrency market: Evidence from cryptocurrency telegram groups.* Journal of Corporate Finance, 56:228–248, 2019. 12

[58] Gandal, Neil, JT Hamrick, Tyler Moore, and Tali Oberman: *Price manipulation in the bitcoin ecosystem.* In *Proceedings of the 2018 Conference on Economic and Financial Computing*, pages 1–7, 2018. 12, 13, 20

[59] Edelman, Benjamin, Tyler Moore, and Tali Oberman: *Detecting pump and dump in cryptocurrency markets.* Journal of Economic Perspectives, 32(2):81–102, 2018. 12, 13

[60] Van Loon, Sander, Harald Vranken, and William Knottenbelt: *Front-running in permissionless decentralized exchanges.* IEEE Transactions on Dependable and Secure Computing, 18(1):305–318, 2021. 13

[61] Bistarelli, Stefano, Maurizio Naldi, Federica Paci, and Fiammetta Rossi: *Front-running and self-trading in permissionless blockchains.* In *2018 IEEE International Conference on Blockchain (Blockchain)*, pages 541–548, 2018. 13

[62] Chai, Daniel, Frank Fehle, and Cameron Truong: *Insider trading in the market for initial coin offerings: Evidence from pre- and post-launch trading.* Journal of Corporate Finance, 56:402–424, 2019. 14

[63] Liu, Yuxin, Xin Su, and Zhong Liu: *Detecting insider trading from blockchain ecosystem.* IEEE Access, 8:161071–161080, 2020. 14

[64] Yang, Sisi, Ling Zhu, Zhe Wu, and Yongfeng Huang: *Spreading bad news or rumors? analysis of cryptocurrency market manipulation on twitter.* IEEE Transactions on Knowledge and Data Engineering, 2021. 14

[65] Feng, Ling, Zheng Li, Kevin Yang, and Chao Zhang: *Cryptocurrency market manipulation: Evidence from twitter.* Pacific-Basin Finance Journal, 64:101384, 2020. 14

[66] Corwin, Shane A. and Paul Schultz: *The role of ipo underwriting syndicates: Pricing, information production, and underwriter competition.* Journal of Finance, 67(5):1767–1808, 2012. 15

[67] Jarrow, Robert A. and Philip Protter: *A dysfunctional role of high frequency trading in electronic markets.* Quantitative Finance, 11(8):1197–1214, 2011. 15

[68] *The cftc orders five banks to pay over $1.4 billion in penalties for attempted manipulation of foreign exchange benchmark rates.* 2018. `https://www.cftc.gov/PressRoom/PressReleases/7874-18`. 15

[69] *Sec charges 14 firms in $14.4 million layering scheme.* 2015. `https://www.sec.gov/news/pressrelease/2015-46.html`. 15

[70] *Two former deutsche bank traders convicted in connection with scheme to manipulate the u.s. dollar libor and euro interbank offered rate.* 2018. `https://www.justice.gov/opa/pr/two-former-deutsche-bank-traders-convicted-role-scheme-manipulate-critical-global` 15

[71] *Cftc orders merrill lynch commodities, inc. to pay $25 million penalty for spoofing in precious metals futures contracts.* 2019. `https://www.cftc.gov/PressRoom/PressReleases/7972-19`. 15

[72] Trillium Management, LLC: *Surveyor-illustrations-template-1.jpg.* `https://www.trlm.com/wp-content/uploads/2016/08/Surveyor-Illustrations-Template-1.jpg`, visited on 2023-06-18. 16

[73] Corcoran, Conor and Paul Green: *Understanding hft spoofing and layering techniques.* Journal of Financial Market Infrastructures, 8(4), 2020. 16

[74] Cheung, Adrian, Wing S. Chow, and Jacky C. K. Cheung: *Understanding high-frequency trading in the cryptocurrency market.* IEEE Transactions on Computational Social Systems, 6(1):47–61, 2019. 16

[75] Trillium Management, LLC: *Surveyor-illustrations-template.jpg.* `https://www.trlm.com/wp-content/uploads/2016/08/Surveyor-Illustrations-Template.jpg`, visited on 2023-06-18. 16

[76] Commission, U.S. Commodity Futures Trading: *Cftc orders mizuho bank, ltd. to pay $250,000 for spoofing and attempted manipulation in the precious metals futures markets.* 2018. `https://www.cftc.gov/PressRoom/PressReleases/7831-18`, visited on 2021-09-17. 17

[77] Lu, David Z.: *Individual accountability for corporate wrongdoing.* Notre Dame Law Review, 96(5):1991–2044, 2021. 17

[78] Schultz, Thomas J.: *Spoofing and manipulation in commodity futures markets.* Fordham Journal of Corporate & Financial Law, 24:1–59, 2019. 17

[79] Andrews, Neil: *The cftc fights spoofing in the futures markets.* The Review of Securities & Commodities Regulation, 51(14):1–14, 2018. 17

[80] Doherty, Robert W. and Kathleen M. Mowry: *Taming spoofing: The pursuit of criminals in the futures markets.* The Review of Securities & Commodities Regulation, 52(17):1–12, 2019. 17

[81] Hevner, Alan, Samir Chatterjee, Alan Hevner, and Samir Chatterjee: *Design science research in information systems.* Design research in information systems: theory and practice, pages 9–22, 2010. 20

[82] Peffers, Ken, Tuure Tuunanen, Marcus A Rothenberger, and Samir Chatterjee: *A design science research methodology for information systems research.* Journal of management information systems, 24(3):45–77, 2007. 20

[83] Cartea, Álvaro, Sebastian Jaimungal, and Damir Kinzebulatov: *Algorithmic trading with learning.* International Journal of Theoretical and Applied Finance, 19(04):1650028, 2016. 20

[84] Chan, Stephen, Jeffrey Chu, Saralees Nadarajah, and Joerg Osterrieder: *A statistical analysis of cryptocurrencies.* Journal of Risk and Financial Management, 10(2):12, 2017. 20

[85] Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin: *Attention is all you need.* Advances in neural information processing systems, 30, 2017. 21

[86] Howard, Jeremy and Sebastian Ruder: *Universal language model fine-tuning for text classification.* arXiv preprint arXiv:1801.06146, 2018. 21

[87] Barocas, Solon, Moritz Hardt, and Arvind Narayanan: *Fairness in machine learning.* Nips tutorial, 1:2017, 2017. 22

[88] Mittelstadt, Brent Daniel, Patrick Allo, Mariarosaria Taddeo, Sandra Wachter, and Luciano Floridi: *The ethics of algorithms: Mapping the debate.* Big Data & Society, 3(2):2053951716679679, 2016. 22