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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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.

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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, which is raised bby analyzing the historical transaction data from a given cryptocurrency. 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

Anomalous transactions pose a threat to the exchange's reputation, potential client acquisition, and trading volume, significantly impacting its revenue model based on transaction taxes. Decreased transactions not only directly affect revenue but also risk regulatory fines for non-compliance, while users may cease trading due to perceived transaction unfairness.

Currently, Mercado Bitcoin relies solely on United Nations Security Council Resolutions (UNSCR) 1267 to freeze funds related to terrorism financing and Interpol fugitives/wanted persons. However, there is a pressing need for a mechanism capable of

analyzing trading data, distinguishing anomalous from non-anomalous transactions. This would enable a human back office to determine if anomalies indicate any form of market manipulation.

1.3   Aims and Objectives

Aim Statement: *This project seeks to examine the trading data of criptocurrencies on Mercado Bitcoin cryptocurrency exchange, to detect anomalies and have a human back office analyze them.*

    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;
- Explore a variaty of anomaly detection techniques on the collected data;
- Evaluate these techniques by deliberate inserting anomalous data and check either or not that the artificial data can be detect as anomalous;
- Compare the results against techniques used on the detection of anomalies on the traditional stock market;
- Collect and debate the results.

1.4   Justification

Mercado Bitcoin has facilitated a total trading volume of 50 billion reais since its 2013 inception, with 200 assets and 3.8 million active clients. Bitcoin constitutes 40% of the $1 trillion in total crypto assets.

    Implementing an anomaly detection mechanism is imperative for enhancing Mercado Bitcoin's revenue, user trust, and compliance with regulators and investors. This effort stands to benefit Brazilian authorities, particularly the *Comissão de Valores Mobiliários* (CVM) and *Banco Central do Brasil* (BACEN). Additionally, it aligns with the recent legislative project, PL 4401/2021, passed by the *Câmara dos Deputados*, introducing increased regulation to the cryptocurrency sector.

Chapter 2

Definitions of Terms

In this section we define basic concepts which are fundamental to the research.

2.1 Cryptocurrencies

In this section, we present viewers with the definition of cryptocurrency, how does a cryptocurrency transaction work and what is an anomaly on this context and the types of anomalies that can raise from cryptocurrency transactions. A more in-depth explanation of Bitcoin and its protocol can be found on appendix a — Bitcoin: A Peer-to-Peer Electronic Cash System.

Digital tokens known as cryptocurrencies enable direct online payments between individuals. Unlike national currencies, which derive value from legal tender status, cryptocurrencies lack legislated or intrinsic value and are essentially valued based on market demand. Bitcoin and Ether are among the most recognized cryptocurrencies, with several others existing in the market.

2.1.1 How Does a Cryptocurrency Transaction Work?

Cryptocurrency transactions involve the transmission of electronic messages across the entire network, containing instructions detailing the parties' electronic addresses, the currency quantity for trade, and a time stamp.

If Alice intends to transfer one unit of cryptocurrency to Bob, she initiates the transaction by broadcasting her instructions through an electronic message visible to all network users. This transaction joins a queue of recent transactions awaiting compilation into a block, which is essentially a group of the most recent transactions. Since the system is not instantaneous, the transaction patiently resides with other recent transactions until they are assembled into a block.

The information within the block is encrypted into a cryptographic code, prompting miners to engage in a competitive process to decipher the code and append the new block of transactions to the blockchain. Upon a miner successfully solving the code, other network users verify the solution, reaching a consensus on its validity. Subsequently, the new block is seamlessly added to the end of the blockchain, confirming Alice's transaction. This confirmation, however, is not immediate, requiring the processing of six blocks of transactions to ensure users' certainty about the success of their transactions.

2.1.2 Anomalies and Cryptocurrency Transactions

Anomaly detection is the scientific pursuit of identifying patterns within data sets that deviate from anticipated behaviors. Such deviant patterns are commonly denoted as anomalies, outliers, discordant observations, exceptions, aberrations, surprises, peculiarities, or contaminants across diverse application domains. Within the domain of anomaly detection, the terms 'anomalies' and 'outliers' are frequently employed, at times interchangeably. This scientific discipline finds broad applicability in various domains, including but not limited to fraud detection in credit cards, insurance, or healthcare, intrusion detection in cyber-security, fault detection in safety-critical systems, and military surveillance for the identification of enemy activities [3].

Anomalies can occur at any level of abstraction, from individual data points to entire systems, and can be caused by a wide range of factors, including human error, software bugs, hardware failures, and malicious activity. As such, on this research we expect to encounter anomalies on the form of fraudulent activities, on purpose or not.

> **Definition 1** *An anomaly is an observation or a sequence of observations which deviates remarkably from the general distribution of data. The set of the anomalies form a very small part of the dataset [4].*

For consistency, we will use the term anomaly throughout this research.

The identification of anomalies in cryptocurrency transactions poses a challenging task, particularly when such anomalies arise from malicious activities. Malicious adversaries exhibit adaptability by manipulating anomalous observations to mimic normal patterns, thereby introducing complexity to the definition of normal behavior. Another obstacle in the realm of anomaly detection in cryptocurrency transactions is the variability in the conceptualization of anomalies across different application domains. For instance, within the medical domain, a slight deviation from the norm, such as fluctuations in body temperature, may constitute an anomaly. In contrast, analogous deviations in the cryptocurrency market domain, such as fluctuations in the value of a specific cryptocurrency,

might be considered normal. Consequently, the direct application of techniques developed in one domain to another is not a straightforward endeavor [3].

2.1.3 Crypto Trading

WIP

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 [5]. 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 [6]. 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 [7].

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 [8]. Cur-

rency manipulation, though legal, may face challenges from other countries. Governments may engage in currency devaluation to enhance their competitiveness [8].

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 [9].

Pump-and-dump schemes typically follow a similar pattern [10]:

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 de-

tection methods. However, the decentralized and anonymous nature of cryptocurrencies poses challenges in effectively combating this form of manipulation [11, 12].

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 [13].

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 [14].

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 [13, 14].

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 [15].

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 [16].

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 [17, 18].

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 [19, 20].

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 [21, 22].

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 [23, 24].

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 [25, 26].
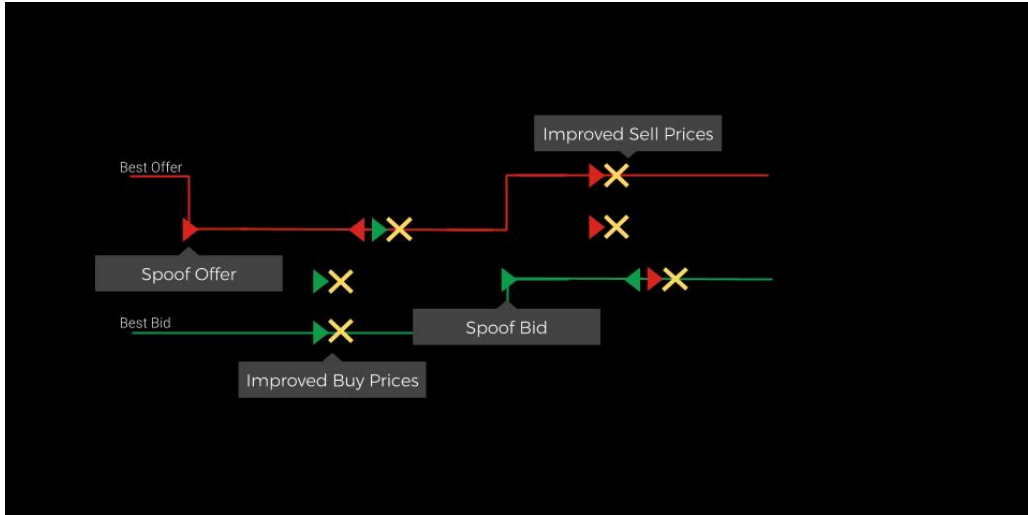

Figure 2.1: A Tipical Spoofing (Reference: [27]).

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 the challenge of detection [28, 29].

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
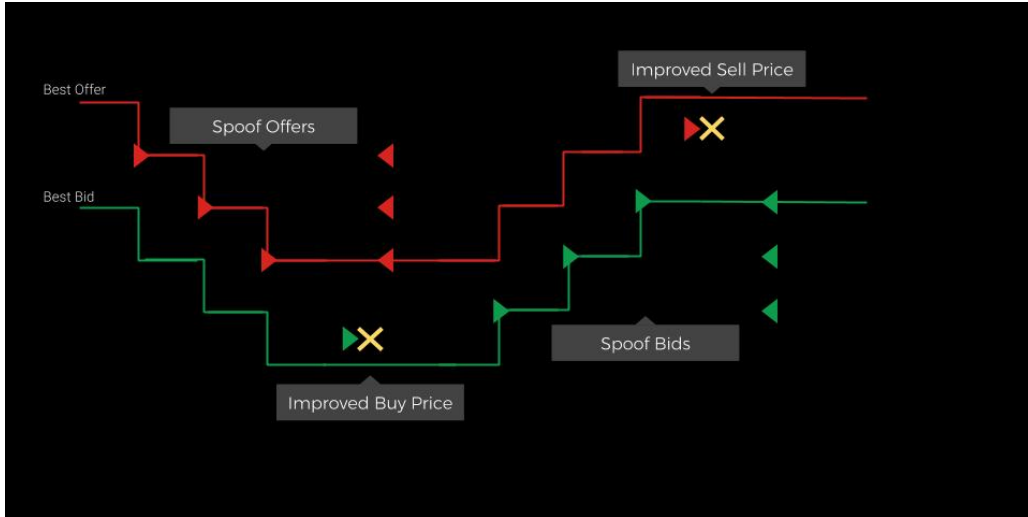
Figure 2.2: A Tipical Layering (Reference: [30]).

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. [31, 32, 33].

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 [34, 35].

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 [36, 37]. 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 [13, 38]. The rapid growth of cryptocurrency markets, including Bitcoin, has highlighted the need for effective tools to detect and prevent such manipulative activities [39]. 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 [40], 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 [41].

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 [42, 43]. 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.
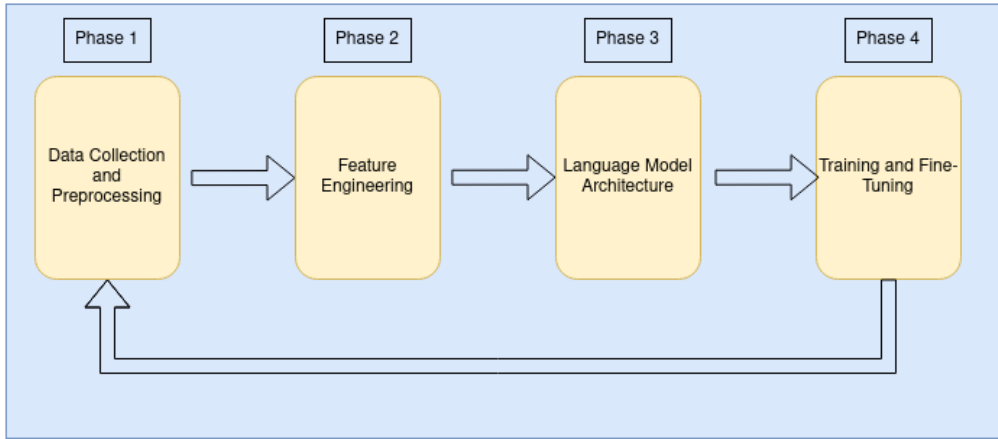

Figure 3.1: Proposed methodology.

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]

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[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.

Chapter 4

Energy-based Flow Classification (EFC)

Money laundering poses a significant challenge to financial institutions, particularly in the cryptocurrency sector, where the pseudonymous nature of transactions provides opportunities for illicit financial activities. Traditional anti-money laundering (AML) systems rely on rule-based detection methods, which often fail to identify novel or evolving fraudulent schemes. To address this issue, machine learning-based classifiers have gained prominence in anomaly detection within financial transactions. Among these, the Energy-based Flow Classifier (EFC) presents a novel approach to detecting both known and unknown fraudulent activities with high accuracy and efficiency.

The Energy Flow Classifier (EFC) is a probabilistic machine learning framework inspired by statistical physics, particularly the Potts model, which historically dealt with atomic spins in a lattice. EFC leverages the concept of "flow energy" to classify network traffic or other data flows [44].

This chapter explores the applicability of EFC in AML on the context of cryptocurrency transactions. It introduces the fundamental principles of EFC, its advantages over traditional methods, and its potential integration into existing AML frameworks.

4.1 How EFC Works

EFC was initially developed for Network Intrusion Detection Systems (NIDS) to recognize both known and unknown attacks. The classifier is built upon statistical physics principles, particularly the Potts model, which estimates probability distributions of normal and anomalous network flows. The primary innovation of EFC is its ability to generalize well while maintaining computational efficiency, making it an attractive option for AML applications where real-time detection of suspicious transactions is crucial [45].

EFC operates by constructing a statistical model that captures the normal behavior of transactional flows. It achieves this through the following core principles:

- **Inverse Potts Model**: Inspired by statistical physics, EFC models interactions between different transaction attributes as energy couplings.

- **Hamiltonian Function**: The classifier assigns an energy score to each transaction based on its deviation from expected behavior.

- **Anomaly Detection**: Transactions with high energy values are classified as suspicious, as they deviate significantly from known benign patterns.

Mathematically, EFC defines the energy of a transaction flow as:

$$H(a_1, ..., a_N) = -\sum_{i,j|i<j} e_{ij}(a_i, a_j) - \sum_i h_i(a_i) \tag{4.1}$$

where:

- a_i represents a feature of the transaction,

- e_{ij} is the coupling strength between features i and j,

- $h_i(a_i)$ is the local field associated with feature a_i.

The statistical model underlying EFC is inferred using the maximum entropy principle:

$$\max_P \left(-\sum_k P(a_1^k, ..., a_N^k) \log P(a_1^k, ..., a_N^k) \right) \tag{4.2}$$

subject to the empirical frequency constraints:

$$\sum_k P(a_i^k) = f_i(a_i), \quad \sum_k P(a_i^k, a_j^k) = f_{ij}(a_i, a_j) \tag{4.3}$$

for all features i, j, ensuring that the model aligns with the observed distribution.

4.2 Model Inference

The process of training an EFC involves learning the statistical distribution of benign transaction flows. This is done by:

1. **Extracting Features**: Transaction data is represented using attributes such as sender-receiver patterns, transaction amounts, and frequency.

2. **Computing Couplings and Local Fields**: The dependencies between different attributes are quantified using a covariance matrix:

$$C_{ij}(a_i, a_j) = f_{ij}(a_i, a_j) - f_i(a_i)f_j(a_j) \qquad (4.4)$$

The couplings are then inferred as:

$$e_{ij}(a_i, a_j) = -(C^{-1})ij(a_i, a_j) \qquad (4.5)$$

3. **Energy Computation**: The energy of a new transaction is calculated using the inferred statistical model:

$$H(a_1, ..., a_N) = -\sum i, j|i < je_{ij}(a_i, a_j) - \sum_i h_i(a_i) \qquad (4.6)$$

4. **Thresholding for Anomaly Detection**: A threshold T is defined based on statistical properties of known benign transactions. Transactions with $H > T$ are flagged as suspicious.

5. **Model Refinement**: The model is periodically updated by incorporating new benign transaction data, ensuring adaptability to evolving transaction patterns.

4.3 Aplying EFC on Elliptic Dataset

Experiments table

Table 4.1: Experiments applied with EFC

Experiment	Description	Methods	Best f1 macro and Method
Experiment 1	Custom EFC python implementation	Contamination	10% contamination with 0.418776
Experiment 2	Labeled and unbalabeled samples	Including labeled samples, unbalabeled samples, excluding aggregates features	All labeled samples with 0.487943
Experiment 3	Unbalanced dataset techniques	Unbalanced Dataset, Equally Distributed Classes, Smote, Random Oversampling and Random Undersampling	Smote with 0.908352
Experiment 4	Feature selection	f_classif with increasing k size	k=10 with 0.685565
Experiment 5	Feature selection and unbalanced dataset techniques	f_classif with increasing k size with smote	smote with k=60 0.8947323

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Supplement I

Appendix

I.1   Bitcoin: A Peer-to-Peer Electronic Cash System

Bitcoin is a decentralized digital currency that operates on a peer-to-peer network called the blockchain. It was introduced in a 2008 whitepaper by an anonymous person or group of people using the pseudonym Satoshi Nakamoto [46]. Bitcoin is not controlled by any central authority, such as a government or financial institution, making it a unique form of currency. It relies on cryptographic techniques to secure transactions and control the creation of new units.

What are the underlying technologies utilized by Bitcoin and what specific events occur during the transfer of a single Bitcoin from one digital wallet to another? In the upcoming sections, we aim to answer those questions.

I.1.1   How Does Bitcoin Actually Work?

Bitcoin's creation was prompted by the need for a secure and decentralized system of transferring value. The solution to this problem involved an intriguing mathematical puzzle that required the invention of new concepts such as digital signatures and cryptographic hash functions.

Creating a new cryptocurrency is a complex process that involves several steps, including developing a consensus mechanism, creating a blockchain, implementing security measures, and ensuring decentralization. To understand how Bitcoin works and identify potential areas for design improvements, it can be helpful to examine the technical details of its underlying protocols [46]. Alternative cryptocurrencies have emerged as a result of different design choices made by their creators, which has led to a diverse ecosystem of digital currencies with varying features and use cases.

While the underlying technology may seem complex to some, it is important to note that using a cryptocurrency does not require an in-depth understanding of its mechanics [47]. Just like swiping a credit card, users can take advantage of user-friendly applications that enable seamless sending and receiving of these digital assets.

The concept of cryptocurrency revolves around enabling individuals to conduct transactions without relying on a centralized entity for trust verification. Typically, when using a credit card to purchase goods or services, one must rely on banks (or a network of banks) to correctly debit the user's account and credit the recipient's account. The majority of currencies are issued by governments, which can exercise some level of control over their respective currencies through means such as adjusting the money supply. As a result, holders of these currencies must place a certain degree of trust in the government issuing them to manage them effectively.

The concept of Bitcoin was inspired by the desire to overcome the limitations of traditional financial systems. According to Nakamoto (2008, p.1) [46]:

> *the root problem with conventional currencies is all the trust that's required to make it work*

To address this issue, Bitcoin was designed as a decentralized digital currency that operates without a central authority or intermediary. The money supply of Bitcoin is fixed and determined by its underlying algorithm, making it resistant to inflation and manipulation. In addition, transactions in the Bitcoin network are recorded on a public ledger called the blockchain, which ensures transparency and accountability. Bitcoin allows for direct peer-to-peer payments without the need for intermediaries, such as banks or payment processors. This property of Bitcoin eliminates the need for trust in a central authority and enables participants to transact with each other directly, thereby reducing transaction costs and increasing efficiency.

The concept of decentralization in trustless payment systems has been subject to debate among readers. However, this discussion is beyond the scope of our current topic. While personal needs for trustless payments may vary, the question of whether such a system is technically feasible remains an intriguing one. Cryptography, which originated from encrypting messages, employs deep mathematical concepts to achieve its objectives. The remarkable effectiveness of cryptographic tools extends beyond confidential communication into other domains. For instance, the development of a decentralized currency presents a significant challenge that can be addressed by applying cryptographic techniques [48].

Creating Your Own Cryptocurrency

One common scenario where distributed ledgers can be useful is when multiple individuals frequently exchange small amounts of money, such as paying for shared expenses like dinner bills. To simplify this process, they may choose to maintain a communal ledger that records these transactions in a manner similar to using physical currency. By doing so, participants can easily keep track of their contributions and settle up when necessary.
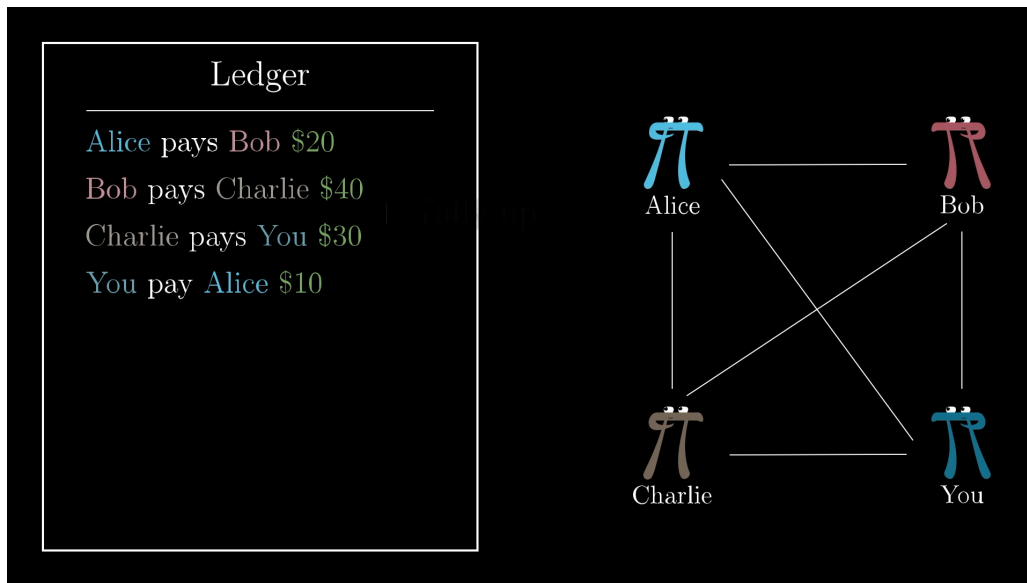

Figure I.1: A ledger is a record of financial transactions, utilized for monitoring the accounts of all parties involved (Reference: [49]).

The proposed ledger system would be a publicly accessible platform similar to a website where users can add new entries. At the end of each month, participants could review the list of transactions and calculate the total sum. If an individual has spent more than they have received, they would contribute that amount to the collective pool, while those who have received more than they have spent would withdraw funds from the pool.

The protocol for participation in the system involves the following steps:

1. Any individual can add entries to the distributed ledger;

2. At the end of each month, all participants gather to reconcile their accounts using physical currency.

However, a potential issue arises with a public ledger that allows any individual to add entries. How can one ensure that Bob does not enter "Alice pays Bob 100" without Alice's approval? There is a Cryptography solution: *Digital signatures.*

I.1.2 Digital Signatures

Digital signatures provide a means to ensure the authenticity and integrity of electronic transactions. The use of digital signatures allow recipients to verify that the information sent by a sender is what they intended to send, thereby establishing trust in the transaction [50].

The concept described here is similar to a handwritten signature, whereby Alice can add a message or proof of approval to a transaction that cannot be easily replicated by others. This is achieved through the use of digital signatures, which are based on cryptographic algorithms and provide a secure method for verifying the authenticity of a message or transaction [51]. The infeasibility of forging a signature is ensured through the use of advanced encryption techniques that make it difficult for unauthorized parties to tamper with or counterfeit digital signatures [51].
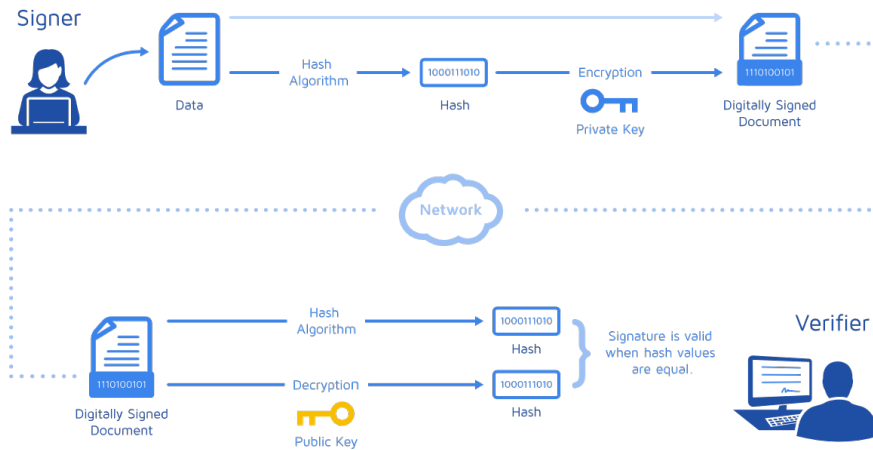

Figure I.2: Digital signature (Reference: [52]).

It may seem counterintuitive at first, but digital signatures can be implemented in a way that prevents forgery. In this context, a digital signature is a function of two elements: the private key, which only the signatory possesses, and the message being signed [48]. This means that even if an attacker were able to copy the initial signature, subsequent attempts to use it would result in a different value due to the unique relationship between the private key and the message.

In cryptography, a signature function is only effective if there exists a verification function to confirm its validity [53]. The mechanism for this involves generating a public-private key pair consisting of two strings of 1's and 0's. The private key, also known as the *secretkey*, is often abbreviated as *sk* while the public key is denoted as *pk*. As suggested by their names, the secret key should be kept confidential [54].

A digital signature scheme can be defined as a set of two operations: one for generating a digital signature on a given message, denoted as Sign, and the other for verifying the authenticity of a purported signature, denoted as Verify. These functions are typically implemented as follows:

1. *Signing function* Sign: This operation takes as input a message $m \in \{0,1\}^*$, and produces a digital signature Sign $\in \mathbb{Z}_q^*$, where q is a prime number. The security of the scheme is typically guaranteed by the assumption that it is computationally infeasible to compute the discrete logarithm in the underlying finite field, $\mathbb{Z}_q$.

2. *Verification function* Verify: This operation takes as input a message $m \in \{0,1\}^*$, a digital signature Sign $\in \mathbb{Z}_q^*$, and the public key (pk, sk), where $pk = g^x$ for some generator polynomial $g \in \mathbb{Z}[X]$ of degree $n-1$ and $x \in \mathbb{Z}_q$. The verification function outputs a Boolean value indicating whether or not the given signature is valid, i.e., Sign$(m) = g^y \mod q$, where $y \in \mathbb{Z}$ is the unique integer such that $g^{y \mod n} \equiv sk \pmod{q}$.

The signing process requires employing the private key. The objective is that if Alice alone possesses her private key, then she is the only individual capable of generating a digital signature. If this key is compromised the security of the system is significantly undermined. The Verify function serves as a means of determining whether a given message bears a valid digital signature generated using the corresponding public key. It should return True when applied to an authentic signature and False for all other signatures.

The security of a digital signature scheme relies on the secrecy of the private key used to generate the signature. However, it is theoretically possible for an attacker to brute-force the public key and find a valid signature by exhaustively trying different potential signatures until one returns true [55]. In the case of Bitcoin's digital signature scheme, there are 2^{256} possible signatures due to the large number of bits in the hash function used for signature generation [54]. However, this number is so large that it makes brute-force attacks on the public key infeasible, providing a high level of security for Bitcoin's digital signatures.

I.1.3 Ledger

In blockchain systems, transactions are recorded on a distributed ledger and secured through cryptographic techniques. Specifically, each transaction needs to be signed by its corresponding private key, which ensures its authenticity and non-repudiation [50]. The signature generated for a given transaction is unique and dependent on the content of that

transaction, making it impossible to reuse signatures from one transaction to another [56]. However, there is an issue with this approach. Suppose Alice signs a transaction, such as "Alice pays Bob \$100", which is then recorded on the blockchain. Although Bob cannot forge Alice's signature on new messages, he could still copy that same line multiple times and submit it to the network. Since the message/signature combination is still valid, these duplicate transactions may be accepted by the network and included in its consensus state [57].
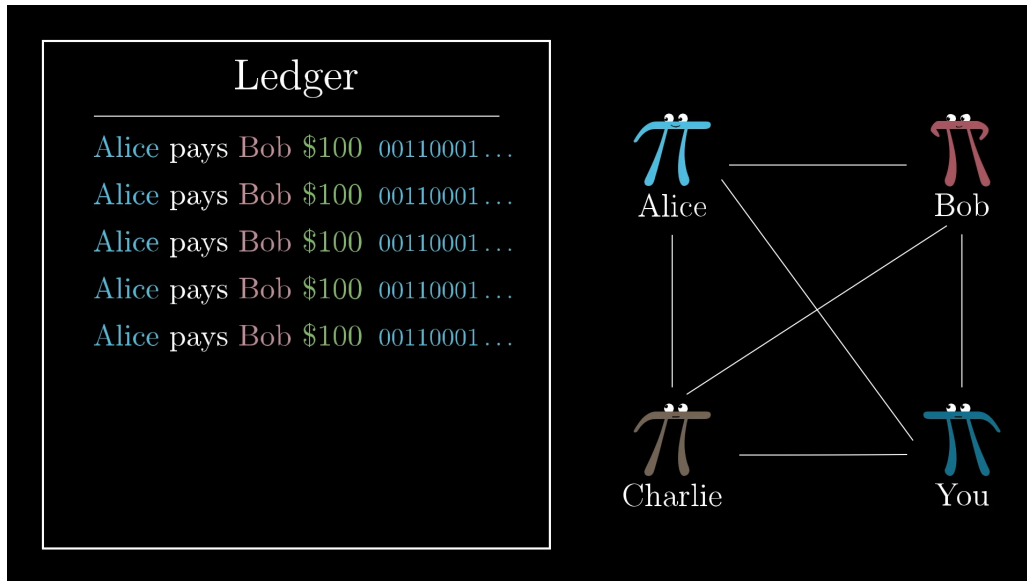

Figure I.3: Anyone can create copies of previous transactions (Reference: [58]).

The development of digital signatures can address the issue of trust in the initial protocol by introducing unique identifiers for transactions and requiring a distinct signature for each transaction. This approach has been proposed and implemented in various cryptographic systems, such as the RSA signature scheme [59] and the elliptic curve digital signature algorithm (ECDSA). The use of digital signatures not only enhances security but also enables efficient verification of the authenticity and integrity of electronic messages.

Removing Cash

The effectiveness of this system relies on an implicit agreement between individuals to uphold their financial obligations. Specifically, participants are expected to pay in cash at the end of each month, despite the absence of a formal enforcement mechanism. However, there is no guarantee that all parties will comply with this arrangement, as demonstrated by instances where one individual (e.g., Charlie) may accumulate significant debt and subsequently fail to fulfill their financial obligations.

In this cashless economic system, it may be necessary to revert to cash to settle up if certain individuals owe a significant amount of money (e.g., Charlie). However, as long as no one falls into debt and the ledger is properly maintained, the use of cash can be avoided. The ledger alone can function effectively as long as there is a mechanism in place to prevent excessive spending.

One strategy for managing a cashless economy without resorting to cash settlements is to have all participants deposit an equal amount (e.g., $100) into the pot, and record the initial distribution of funds on the ledger. For example, Alice would receive $100 in the first transaction, while Bob would receive $100 in the second transaction, and so on. By using this approach, individuals can maintain their financial balance without the need for cash transactions.

Now that we are under a cashless economic system, it is important to prevent double-spending attacks where a user attempts to spend the same cryptocurrency more than once. One way to accomplish this is by verifying that transactions are valid before they are added to the ledger. Specifically, if all users on the network start with zero balance ($0) and the first two transactions are of $100 value (Charlie pays Alice $50 and Charlie pays Bob $50), then a third transaction where Charlie pays You $20 would be invalid. This is because it violates the rule that a user cannot spend more than they have in their account.
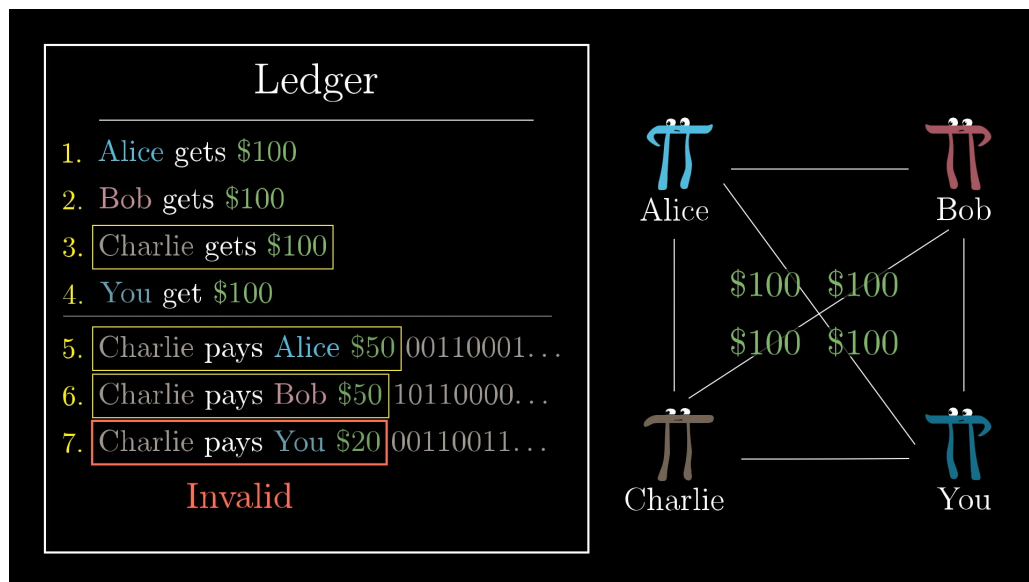

Figure I.4: In this new system, we don't allow people to spend more than they have. (Reference: [60]).

It can be noted that the requirement to ascertain the legitimacy of a transaction necessitates knowledge of the entire transaction history. This principle applies not only to

traditional financial systems but also to decentralized digital currencies, although opportunities for improvement is present.
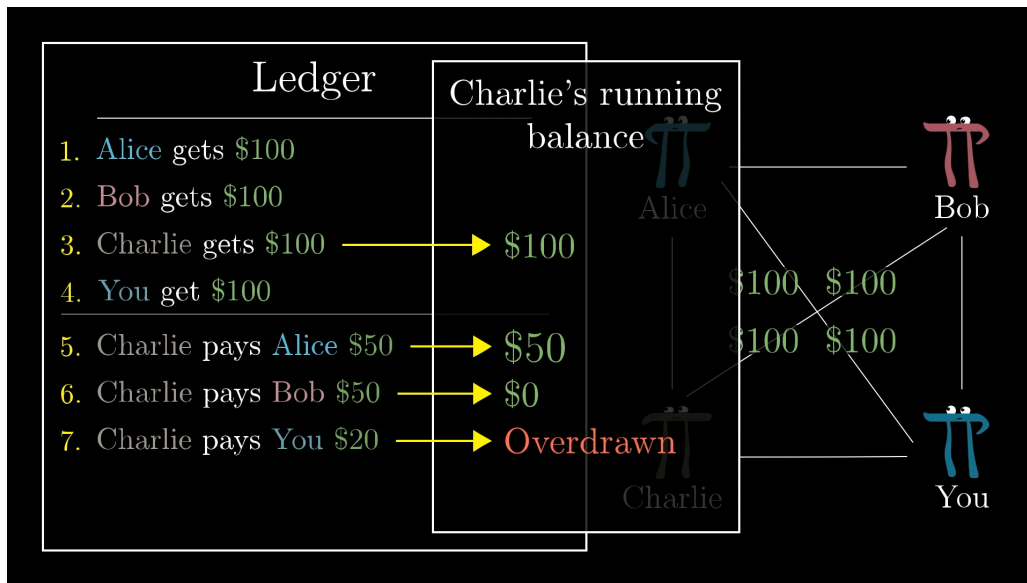

Figure I.5: Now verifying a transaction requires checking the entire ledger history to make sure nobody overdraws. (Reference: [61]).

The use of the above ledger system appears to dissociate it from physical cash transactions. If everyone in the world were to utilize this ledger, one could theoretically conduct all financial transactions solely through the ledger without any need for conversion to United States Dollars (USD). Many individuals currently perform digital transactions exclusively while occasionally using physical cash. The latter scenario involves a more intricate system of banks wherein the balance on a digital account can be converted into USD. However, if one and their associates were to completely detach their ledger from USD, there would be no guarantee that having a positive balance in the ledger could translate into physical currency in hand. To accentuate this point, one can stop using the $ sign, and digital quantities, on the ledger can be referred to as "Ledger Dollars" (LD).

Individuals possessing Ledger Dollars have the liberty to convert them into US dollars at their discretion. An example involves Alice offers Bob a zero-value US dollar bill in exchange for him adding and signing a transaction entry to the shared ledger, wherein Bob pays Alice ten units of Ledger Dollar value. However, the protocol does not explicitly guarantee the occurrence of such exchanges. Instead, it operates more similarly to foreign currency exchange in an open market where 10LD is its own independent entity. Additionally, if there is high demand for inclusion within the ledger, a transaction of 10LD may require a non-zero amount of physical cash. Conversely, if there is a low demand for participation, it may require only a minimal amount of physical cash.

Our ledger has been transformed into a form of currency that operates within a closed system, allowing for peer-to-peer transactions between individuals without the backing of a state or taxation imposed in the form of Ledger Dollars. It is important to recognize that, at its core, cryptocurrency can be viewed as a ledger that records the history of financial transactions, serving as the currency itself. The concept of possessing Bitcoin is simply represented by a positive balance on the Bitcoin ledger, which is associated with a secret key. This differs from traditional currency systems where money enters the ledger through cash transactions. In the case of Bitcoin, the process for introducing new money into the ledger will be discussed in more detail shortly. However, it is important to note that there are fundamental differences between Ledger Dollars and true cryptocurrencies.

Distributing The Ledger

The distributed nature of the blockchain technology used by the ledger system necessitates the use of a centralized platform for public access and modification of the ledger's contents. However, this raises concerns regarding the trustworthiness of the entity responsible for hosting the website and regulating the rules governing the addition of new entries to the ledger. In particular, it is important to identify and evaluate the credibility of the entity that controls the website and establishes the protocols for updating the ledger.

To eliminate trust in a centralized system where one ledger is maintained, we will replace this with a decentralized approach, where each individual will maintain their own copy of the ledger. This will enable transactions, such as "Alice pays Bob 100 LD" to be broadcasted and recorded on personal ledgers by all parties involved in the network.

The distributed ledger technology employed by Bitcoin involves the broadcast of transactions by users, which are then recorded on a decentralized set of records. This eliminates the need for trust in a central authority. However, this system is problematic due to the possibility of disagreement among participants regarding the correct ledger. For example, when Bob receives a transaction "Alice pays Bob 10 LD", how can he be certain that everyone else has received and believes in the same transaction? If even one person does not know about this transaction, they may not allow Bob to spend those 10 Ledger Dollars later.

The verification of the integrity and consensus of a blockchain network relies on a distributed ledger system where all participants maintain a copy of the same transaction history. The trustworthiness of this system is predicated on the assumption that all nodes will accurately record and remember past transactions, which may be subject to potential inconsistencies or discrepancies in the event of faulty or malicious behavior. Therefore, it is essential to establish a mechanism for ensuring that the distributed ledger remains consistent across all participating nodes. The solution proposed by Satoshi Nakamoto in 2008
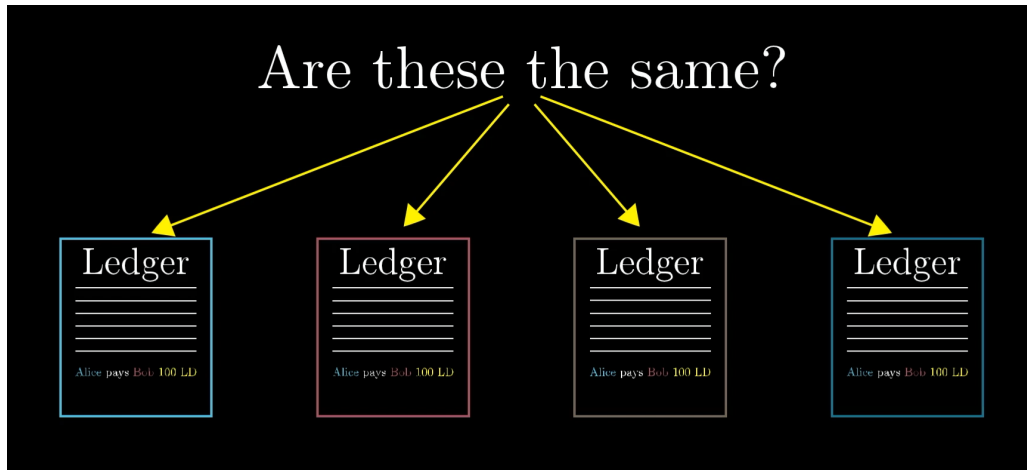
Figure I.6: If everyone keeps a unique copy of the ledger, how can we ensure that everybody agrees on what it should say? (Reference: [62]).

for decentralized systems was a method to validate the validity of a growing document, such as a ledger, without relying on a central authority. This problem was solved through the use of computational work to determine trustworthiness, where the ledger with the most computational effort invested in it is considered legitimate. The idea is that if an individual attempts to manipulate the ledger, it would require an impractical amount of computational power, making fraudulent transactions computationally infeasible. This concept forms the core of Bitcoin and other cryptocurrencies.

I.1.4 Hash Functions

Cryptographic hash functions are the primary tool utilized by Nakamoto's solution to this puzzle. These functions take in arbitrary messages or files as input and produce a fixed-length string of bits referred to as the "hash" or "digest" of the message, which is intended to exhibit randomness. The output of this process is deterministic and consistent for a given input, but minor alterations to the input can lead to drastically different hash values.

The property of unpredictability in the output changes when slightly changing the input is what makes SHA256 a cryptographic hash function [63]. This means that it is computationally infeasible to compute the original message from its hash value in reverse direction [64]. Therefore, given a specific hash value such as $1001111100111100\ldots$, there is no efficient method to determine the corresponding input message other than brute-force guessing and checking with random inputs.

Given the provided function, what is the empirical evidence indicating a significant correlation between a specified set of Bitcoin transactions and an exceptional computational expenditure? *Proof-Of-Work*.

I.1.5 Proof-Of-Work

The task described involves manipulating a collection of transactions (enclosed within a container), whose hash value is computed utilizing the SHA256 algorithm. The objective is to modify a specified element within the container, such that the resulting hash commences with at least six consecutive zeros.

Achieving a solution to this problem is indeed possible, albeit requiring a considerable amount of time. Due to the inherent unpredictability of the hash function's output, the prevailing method for tackling this challenge remains a process of trial and error [65].

As the number of required leading zeroes increases, the difficulty of the problem escalates exponentially. Consider a scenario where an individual presents you with a list of transactions and asserts that they have identified a special number. They claim that by appending this number to the end of the transaction list and applying the SHA256 hash function to the entire sequence, the resulting output will exhibit 30 leading zero bits.

Assessing the level of difficulty involved in discovering the aforementioned number necessitates a thoughtful analysis. It is evident that the task likely posed significant challenges. When considering a randomly selected message, the probability of the resulting hash beginning with 30 consecutive zeroes is 1 in 2^{30}, which corresponds to approximately 1 in a billion [65]. Consequently, it is highly probable that the individual in question had to iterate through approximately one billion distinct guesses before successfully identifying this specific value.

Nevertheless, what proves intriguing is that once the number is known, its verification as a hash commencing with 30 zeros can be efficiently conducted. This verification process offers the ability to ascertain the substantial effort expended by the individual without necessitating the replication of the original labor. Termed as *proof-of-work*, this number holds significance.

It is crucial to emphasize that the entirety of this endeavor is intrinsically linked to the underlying list of transactions. Even a slight modification to any transaction would result in a completely altered hash, compelling a full repetition of the laborious process to identify a new number that yields a hash with 30 zeros [46].

Figure I.7: There is no better way than guess and check for the special hash (Reference: [66]).

I.1.6 Blockchain

A distributed ledger system is composed of multiple nodes that broadcast transactions. To ensure consensus on the correct ledger, it is necessary to develop a mechanism that allows all nodes to agree on the validity of each transaction [67].

The core concept of the original Bitcoin paper [46] is based on the assumption that a distributed ledger will be trusted if it has been subject to a large amount of computational effort. This idea is implemented through the use of the many-zeroes game, which involves proving that a particular block in the chain contains a hash that is difficult to reverse-engineer.

Rather than hashing the entire ledger repeatedly, it is more efficient to allow for the accumulation of computational effort over time. Transactions are grouped into blocks and added to the chain in a linear fashion, with each new block containing a reference to the previous one. This approach allows for the creation of a tamper-evident history of transactions that is trusted by network participants due to the large amount of computational work required to manipulate it.

The block is a collection of transactions enclosed with a unique identifier, known as proof-of-work (PoW), which serves as evidence of the computational effort expended in validating the block. In PoW schemes, the miner must solve a complex mathematical problem to validate the block and add it to the blockchain. The difficulty level of this problem is determined by the target number of leading zeros required in the hash value of the block.
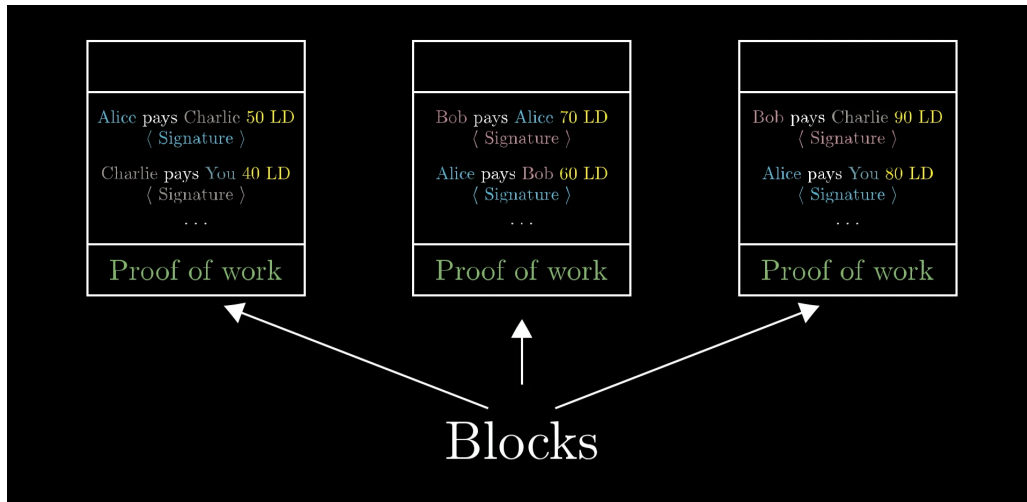
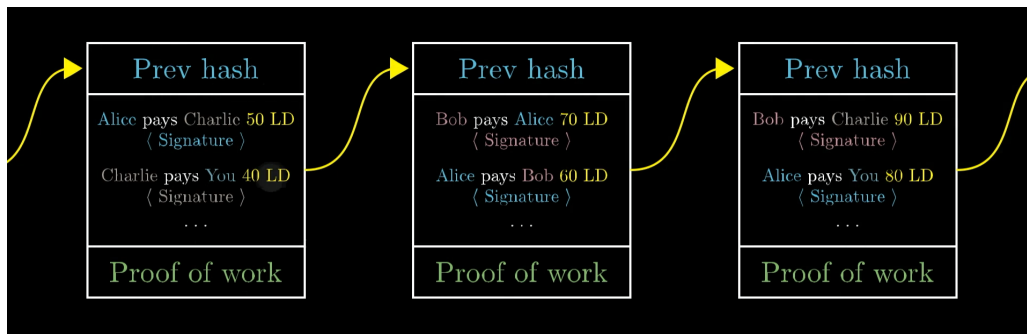Figure I.8: Blocks on a blockchain (Reference: [68]).

Figure I.9: Because blocks are chained together like this, instead of calling it a ledger, this is commonly called a "blockchain" (Reference: [69]).

A block is considered valid if it contains a proof-of-work (PoW) value, analogous to how a transaction is only considered valid when signed by its sender. Additionally, maintaining the integrity of the blockchain requires that blocks are not rearranged as this would disrupt the transaction history. To address this issue, each new block must begin with the hash of the previous block (hash-based chain), ensuring that the order of the blocks remains consistent.

Block Creators: Miners

To maintain the integrity of our ledger after it has been split into blocks, we have introduced a new process for adding new transactions. This involves grouping together transactions into blocks and computing a proof of work. As part of our updated protocol, anyone in the world is allowed to act as a "block creator". The responsibility of the block creator is to listen for broadcasted transactions, collect them into a block, and then

perform a significant amount of computational work to find a special number that will result in the hash of the block starting with 60 zeros. This computed hash value is then broadcasted to the network as proof of work [70].

A special transaction can be included at the beginning of each block, where the creator is rewarded with a predetermined amount of digital currency. This practice has been suggested as a means of compensating individuals for their efforts in constructing blocks within a distributed ledger system [71].
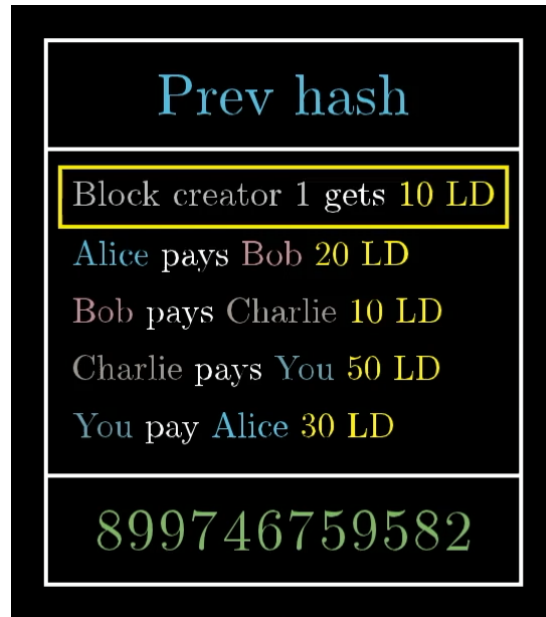

Figure I.10: Block reward (Reference: [72]).

The block reward is a unique exception to our usual transaction acceptance rules in the Ledger Dollar economy, as it does not require signature verification and increases the total number of currency units with each new block.

The process of creating blocks, known as "mining", involves a significant amount of work and introduces new currency into the economy. However, when discussing miners, it is essential to understand that they are primarily focused on listening to transactions, constructing blocks, broadcasting them, and receiving newly minted currency as a reward for their efforts.

For miners, each block can be thought of as a miniature lottery where individuals guess numbers rapidly until one person finds a combination that results in a hash starting with many zeros, earning the resulting reward. In contrast to mining, non-mining Bitcoin users no longer need to record all individual transactions on their personal ledger. Instead, they can simply monitor block production and rely on the fact that these blocks contain veri-

fied transactions. This approach is more manageable than maintaining a comprehensive transaction ledger.

In the consensus algorithm used by Bitcoin and other cryptocurrencies, a mechanism known as the "longest chain rule" is employed to resolve potential conflicts between competing blocks. Specifically, if two miners broadcast distinct blockchains with conflicting transaction histories, the system defers to the one that has been the longest in terms of cumulative proof-of-work effort expended on it, which is assumed to be more resistant to manipulation [73]. If there is a tie between two competing blocks, it may be necessary to wait for additional information to determine which block is longer. This process relies on the assumption that the longest chain represents the most widely accepted version of the blockchain. However, this approach has been subject to criticism due to its reliance on proof-of-work mechanisms, which require significant computational effort and can lead to centralization.

Attempt Fraud On The Blockchain

To evaluate the trustworthiness of this method, it is instructive to consider what steps an individual, such as Alice, would need to take in order to deceive the system. In particular, suppose that Alice desires to purchase an item from Bob for 100 Ledger Dollars (LD), but does not actually possess those LDs. She might attempt to send a block to Bob containing a line indicating "Alice pays Bob 100 LD" without broadcasting this block to the broader network. By doing so, Bob would believe that he had been paid and provide Alice with the item she desires. However, at a later time, Alice could re-enter the economy and spend those same 100 LD elsewhere. When Bob attempts to spending those same 100 LD, other individuals in the network may not recognize them as valid, leading to the potential for deception to be detected.

The process of creating a fraudulent transaction in a blockchain network requires a valid proof-of-work (PoW) that is found before other miners who are listening to the same set of transactions as the attacker, each working on their own block. This is a difficult task but can be accomplished if the attacker has a significant portion of the network's computation power. If Alice is able to find the PoW before other miners, she can create a fraudulent transaction and present it to Bob (but not to anyone else) [74].

However, Bob will continue to receive broadcasts from other miners, and Alice did not inform these miners about the block she produced for Bob. Therefore, they will not include this block in their own versions of the blockchain. As a result, Bob will be hearing conflicting chains: one from Alice and another from everyone else [75]. According to the protocol, Bob always trusts the longest chain he knows about, which may create challenges for detecting and resolving fraudulent transactions in the network.

The probability of Alice's computational resources being smaller than the combined computational resources of the rest of the network is high, and as a result, it is more likely for the rest of the network to find a valid proof of work for their next block before she does. Additionally, if Alice has less than 50% of the total computation on the network (which is highly probable), she will outpace everyone else indefinitely will be nearly impossible [46].

Eventually, when Alice fails to maintain her chain longer than the rest of the network, Bob will reject what he is hearing from Alice and follow the longer chain that everyone else is working on. This is because creating blocks requires significant computational effort, making it extremely difficult for any individual or group to manipulate the consensus [76].

It's worth noting that while building a single fraudulent block may be possible, maintaining the lie for an extended period is challenging. Therefore, users should exercise caution and wait for several new blocks to be added on top of a newly discovered block before trusting it as part of the main chain. By doing so, they can ensure that they are not being tricked by a malicious actor attempting to manipulate the network [77].
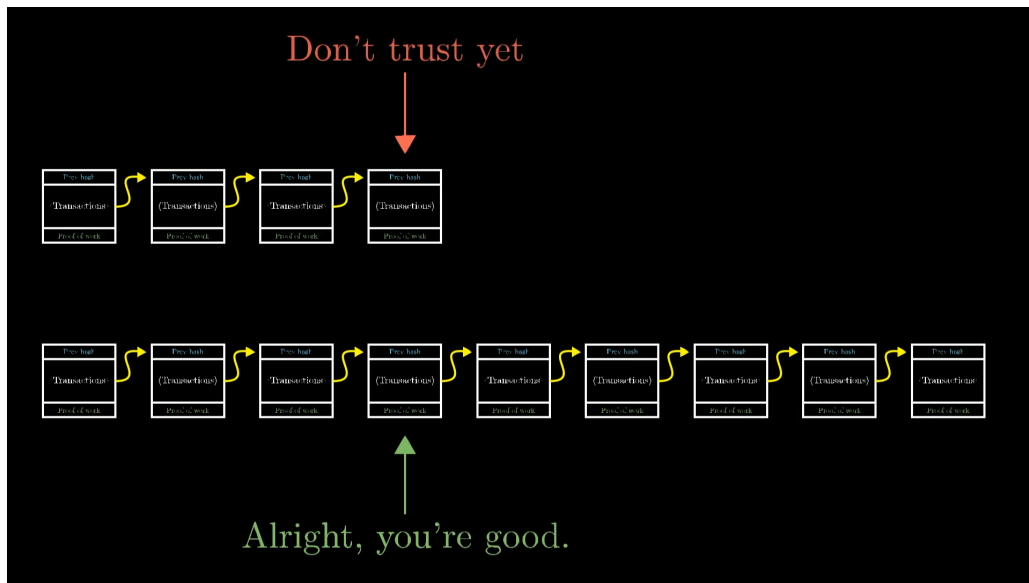

Figure I.11: Blocks are most trustworthy when they aren't brand new (Reference: [78]).

Ledger Dollars vs. Bitcoin

The distributed ledger system based on proof-of-work, as demonstrated by Bitcoin and other cryptocurrencies, involves a mining process where miners compete to solve a computational puzzle in order to validate transactions and add them to the blockchain. This is accomplished through the use of hash functions, which are designed to be difficult to reverse engineer, thereby ensuring the integrity of the distributed ledger [79]. The proof-

of-work challenge may involve finding a special number that will make the hash of the block start with 60 zeros. However, in practice, this is achieved by systematically changing the number of zeros so that it takes approximately 10 minutes for miners to find a new block [46].

As a result of this process, a block reward is awarded to the miner who successfully validates a block. Initially, the reward was set at 50 Bitcoin per block, but it has since been reduced to 6.25 Bitcoin per block every 210,000 blocks [46]. However, miners can also earn transaction fees by including them in the validation process of transactions.
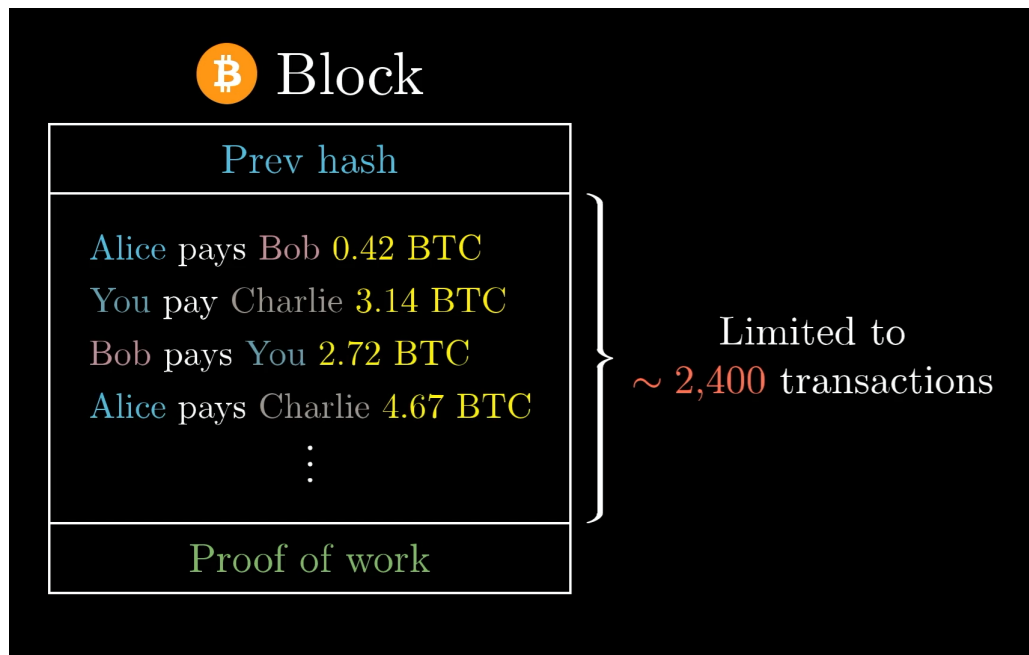

Figure I.12: Transactions on a bitcoin blockchain is limited (Reference: [80]).

Considering Bitcoin's objective of approximately one block addition per 10 minutes, its processing capacity is constrained to about 4 Bitcoin transactions per second, with some variability. By comparison, Visa handles an average of approximately 1,700 transactions per second, with the capability to process over 24,000 per second. The relatively slower processing speed of Bitcoin leads to higher transaction fees, as they determine the selection of transactions included in new blocks by miners. Moreover, Bitcoin has faced criticism for its significant energy consumption. While the proof-of-work concept effectively combats fraud, it necessitates an immense allocation of resources for block mining.

According to the Cambridge Bitcoin Electricity Consumption Index, the present annual electricity consumption for Bitcoin mining (as of 2021) is estimated at around 115 Terrawatt-Hours. To provide context, this consumption surpasses the energy usage of the entire country of Finland. Since 2008, an alternative approach to proof of work, known

as "proof of stake," has emerged, offering a substantial reduction in energy requirements. Several newer cryptocurrencies have embraced this methodology [81].

I.2 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 [46]. 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?

I.2.1 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 [82].

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 [83]. 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 [84].

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 [85]. 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 [86].

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 [87]. 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 [82, 88]. The more easily accessible an item is, the lower its perceived worth [89]. 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 [90, 91].

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 [92, 93]. 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 [94]. 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 [95]. 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 [96]. 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 [97]. 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 [98]. 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 [99]. 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.

I.2.2   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 [100]. 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 [101]. 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 [102, 103].

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 [98, 104]. 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 [104]. 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, [105], 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 [106]. 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 [107]. 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 [108]. This substantial increase in the money supply with the country's output has raised concerns regarding the potential for significant price inflation [109]. 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 [110]. 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 [111, 112].

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 [113]. 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 [114]. 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 [115]. 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 [116]. Consequently, the relative attractiveness of alternative income sources may influence individual's decision-making regarding employment prospects [117].

The United States had accumulated a staggering national debt of \$29 trillion before 2020, an astounding and challenging figure to comprehend [118]. 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 [119]. 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 [120]. 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 [119]. 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 [121].

Through government injections, banks are empowered to expand their lending activities, thereby increasing interest income and fostering economic growth [121]. 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 [122]. 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 [123]. 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 [124].

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**.