PREDICTING BITCOIN PRICE FLUCTUATIONS THROUGH ON-CHAIN DATA AND WHALE-ALERT TWEET ANALYSIS WITH Q-LEARNING ALGORITHM

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Annotation. As cryptocurrency adoption, particularly Bitcoin (BTC), grows in the digital economy, understanding its volatility becomes increasingly crucial. This paper addresses this by exploring the unpredictable nature of the cryptocurrency market, focusing on Bitcoin trend forecasting using on-chain data and whale-alert tweets. Utilizing a Q-learning algorithm, a form of reinforcement learning, the study examines factors such as transaction volume, network activity, and major Bitcoin transactions highlighted by whale-alert tweets. The results show that integrating on-chain and Twitter data enhances the algorithm's ability to predict Bitcoin trends. This research provides valuable insights for investors, aiding in more informed Bitcoin investment decisions and contributing to cryptocurrency risk management.

Keywords: *Bitcoin trend prediction; data features; historical price, CryptoQuant data; sentiment analysis; Q-learning*

INTRODUCTION

Bitcoin has become a subject of extensive debate and interest among various stakeholders, including investors, politicians, and the media. Since its dramatic price increase from $1 to $20,000 in January 2017, just a few years after its introduction in 2009, Bitcoin has gained recognition worldwide as a potentially valuable asset. However, its decentralized nature, privacy implications, and severe volatility, especially compared to traditional investments, have elicited considerable concerns within the political domain. Nevertheless, the potential for substantial returns has consistently drawn investors, leading to a remarkable value of over $64,000 as of November 12, 2021, a significant leap from its 2017 peak of $20,000. Parallel to this value appreciation, interest in Bitcoin and other cryptocurrencies has also surged noticeably. Notably, mega-companies, such as Tesla, have contributed to this trend by accepting cryptocurrencies as a legitimate form of payment. Similarly, large-scale financial institutions and tech giants, including Apple, have reportedly been considering incorporating Bitcoin transactions into their payment infrastructure, such as Apple Pay [1]. Even individuals initially skeptical due to the steep drop in Bitcoin value in 2018 have started to revisit the idea of investing in Bitcoin. However, while the favorable news about cryptocurrencies continues to increase, and the foundation of the cryptocurrency market seems to be becoming more robust, the Bitcoin market retains its inherent volatility. This makes it inherently riskier than traditional assets. Large corporations with substantial funds, such as Apple and

Tesla, can mitigate downside volatility to some extent. However, individual investors with limited time and resources may be significantly impacted by even minor fluctuations in cryptocurrency value. A delayed response to a market crash can lead to disastrous financial losses. Hence, the ability to predict Bitcoin trends is paramount, providing critical insights into potential market behavior and enabling informed buy or sell decisions. In this context, the ability to predict trends in Bitcoin's value becomes important. Accurate trend prediction can enable investors to anticipate market behavior, assisting them in making informed decisions about when to buy or sell Bitcoin. Businesses that accept Bitcoin as payment can also greatly benefit from these predictions, as they can leverage this information to manage their risk and make better decisions about handling their Bitcoin holdings.

In achieving the precise predictions regarding Bitcoin's value trends, machine learning algorithms have emerged as a game changer. These algorithms analyze vast amounts of historical and real-time data, identifying patterns and relationships that might be imperceptible to the human eye. Machine learning models, such as regression analysis, neural networks, and decision trees, are adept at processing this multitude of data points, refining their predictions with each new piece of information. Furthermore, Deep Learning techniques, which are a subset of machine learning, have shown significant promise in different arenas as well [2]–[4].

Given the fact that their ability to analyze data in multiple layers and dimensions, techniques like Long Short-Term Memory (LSTM) networks are particularly suited for time-series predictions, which is essential for forecasting financial trends like Bitcoin's price movement. By harnessing the power of these algorithms, one can gain a competitive edge in anticipating market behavior, leading to more strategic investment decisions concerning Bitcoin and other cryptocurrencies. Given the importance of trend prediction for effective risk management in Bitcoin investment, our study aims to devise a predictive model based on the fundamental economic principle known as "The law of supply and demand." This law posits that the price of a good or service is determined by the balance of its supply and demand. When demand is high and supply is low, prices will rise. Conversely, when supply outpaces demand, prices fall. This balance of supply and demand, and its impact on price, will continue to be a major factor in market behavior, and understanding this balance is crucial for businesses and investors to make informed decisions. In this study, we offer three main contributions. Firstly, we construct a comprehensive dataset that includes two types of data indicating Bitcoin market demand: on-chain data and whale-alert tweets. The on-chain data provide intricate details of each blockchain transaction, such as the number of Bitcoins sold and bought in a particular timeframe, from which wallet to which wallet, and the fees paid. The whale-alert tweets, on the other hand, are extracted from the Twitter account @whale_alert [5], which monitors and publishes significant daily cryptocurrency transactions in real time. Secondly, we investigate the predictive capability of this unique dataset for anticipating future trends in Bitcoin. To do this, we address the problem as a reinforcement learning

(RL) task, framing it within a Markov Decision Process (MDP). In this framework, each row of the dataset representing one day serves as a state, the change in trend status (whether the price will increase, decrease, or hold its value) represents an action, and the model receives a reward of +100 for a correct prediction and -100 for an incorrect one. As the state transition probability is often unknown in practical situations, we utilize the Q-learning algorithm, one of the most prevalent model free reinforcement learning algorithms. For our third contribution, we introduce an innovative approach to predicting Bitcoin trends by integrating the Q-learning algorithm with on-chain data and whale-alert tweets. This unique combination of an advanced machine learning algorithm and diverse data sources is an attempt to bring granularity and real-time responsiveness to Bitcoin trend prediction. Furthermore, we believe our research is crucial in an era where the implications of cryptocurrencies continue to expand across various sectors of society. From individual investors to large corporations, understanding the trends and dynamics of the Bitcoin market can lead to more informed and strategic decisions. As such, our research does not only contribute to the academic field but also has a tangible impact on the real-world practices of investing in and utilizing Bitcoin.

RELATED WORK

With the rise of Bitcoin in mainstream financial markets, numerous studies have sought to understand its value and the factors that determine its price. Early research efforts focused on analyzing the variables that influence Bitcoin's price, including the price of gold [6], indicators of inflation or employment rate [7], [8], historical prices of stocks [9], and sentiment derived from social media and news [10], [11]. The increasing participation of large corporations, investment banks, and hedge funds in Bitcoin investments led to the emergence of the "Digital Gold" concept [12]. This heightened institutional interest has prompted more research into trading algorithms similar to those used in the stock and derivatives markets. Consequently, price prediction, an essential component in the development of these trading algorithms, has garnered increased attention. Researchers and quantitative traders have been employing problem-solving algorithms like machine learning and deep learning to improve the accuracy of price predictions. These studies primarily focus on variables that can impact Bitcoin prices, such as trading volume, macroeconomic indicators, and sentiment. Other studies have used on-chain data and Twitter data to forecast Bitcoin trends and volatility. Table 1 provides a summary of these related studies, detailing the algorithms and methods used in each. This overview helps to place our research within the broader context of existing literature in this field.

On-Chain Data. The Bitcoin market differs significantly from traditional stock markets, with one of the main differences being the transparency provided by blockchain technology [13]. Because Bitcoin is a permissionless blockchain, it uses an open-data structure. Therefore, analysis of the data on the blockchain can provide tools that can further enable an understanding of the underlying network and its usage, providing valuable information on the user, miner behavior, and other activities on the blockchain

[14]. Transparency is one of the main features of Bitcoin trading because it allows traders to access the complete state of the order book and all trading histories, although trading is pseudonymous. Moreover, it provides unique opportunities for price and volatility prediction by providing access to on-chain data, such as details of each transaction, mining difficulty, and block size [15], [16]. These details provide valuable insights into future price movements [17]. An examination of the statistical attributes of cryptocurrency pricing was conducted using blockchain data, primarily drawing upon the features of the Ethereum network. The findings revealed a strong correlation between price and hash rate, difficulty, and transaction cost [18]. However, public blockchain data have become extremely large and are rapidly growing, with a size of 248.93GB in 2021 [19]. To overcome the challenge of processing this substantial volume of information, various scholars have suggested open-source tools to extract crucial details from popular blockchain platforms, such as Bitcoin and Ethereum [20], [21]. A recent study presented a framework that concentrated on collecting and examining datasets from Ethereum and made the collection of datasets available for developers and researchers to study user behavior and other blockchain system activities [22]. The current literature on the utilization of various types of cryptocurrency data, including on-chain data for forecasting purposes, remains in its developmental stages. Despite this, a number of studies have illustrated the potential of on-chain data in predicting cryptocurrency prices.

For instance, Kim et. al. [16] demonstrated the utility of on-chain data for predicting Bitcoin prices by employing a self-attention-based multiple long short-term memory model (SA-LSTM). Similarly, Jagannath et. al. [15] utilized a self-adaptive LSTM model and on-chain data to predict Ethereum prices. They disclosed significant correlations between on-chain characteristics and Ethereum price, such as transaction rate, smart contract supply, block difficulty, and hash rate. Further investigations into the relationship between on-chain transaction activity and volatility have also been highlighted in the literature [23]. A recent study by Casella et. al. [24] aims to illustrate how on-chain data can be leveraged to detect cryptocurrency market regimes, such as bull and bear market phases, as well as minimums and maximums. They posit that forecasting these data can provide optimal asset allocation strategies for long-term investors. Bhatt et. al. [25], on the other hand, have integrated on-chain data with crypto market data and corresponding social media data in their pursuit to improve price prediction. Their use of the Multi-Modal Fusion model resulted in a reported F1 score accuracy of 0.85.

In contrast to these studies, Morillon et. al. [26] utilized CryptoQuant on-chain data to explore the profitability of a trading strategy developed from the Stock-to-Flow (S2F) model. Their findings indicate a significant relation between the S2F ratio and Bitcoin prices. Olise et. al. [27] reported improved forecasting accuracy by using different on-chain data such as the number of active network addresses, transactions, and hash rates in combination with the RNN-LSTM model.

Raheman et. al. [28] focused on developing a cryptoportfolio management agent that leverages on-chain data for predicting price trends and volatility. The goal of this body of work is to build a predictive model for volatility, undertake an exhaustive analysis of the patterns present in the data, and pinpoint the relationships between future prices and the type of data utilized in these studies.

Despite advancements in the use of on-chain data for price predictions, the existing body of work exhibits some significant limitations. Many studies tend to use an indiscriminate mix of on-chain data, lacking a defined criteria for their selection. This broad approach has the potential to introduce noise, thereby reducing the predictive precision. Moreover, certain models, exemplified by the Stock-to-Flow (S2F) model [26], exhibit a constrained focus, prioritizing specific trading strategies and potentially sidelining the wider value embedded within on-chain data. There's also a clear void in the form of a lack of comprehensive analysis. For instance, while [28] explored crypto-portfolio management using on-chain data, a deep and systematic examination of data patterns and their potential correlation with future prices was not presented.

In response to these gaps, our study adopts a meticulous approach, homing in on seven specific on-chain data types that we identified as paramount for predictions. This focused approach intends to sift through the overwhelming volume of blockchain data, eliminating the distractions of less pertinent information. Pairing this with methodological enhancements, we aspire to encompass a wide scope while preserving prediction accuracy. It's our belief that this nuanced and targeted approach will unveil deeper insights, casting light on patterns previously veiled in the expansive sea of blockchain data.

Twitter Data For Price Volatility. Notably, CryptoQuant data provides comprehensive information on aggregated on-chain data, miner data, and more but does not include transactions made by large crypto-walk holders known as crypto-whales. The cryptomarket is known for its volatility, which can be partially attributed to the effects of large transactions by cryptowhales. The price of Bitcoin is not only influenced by the average inflow but also by the public attention given to specific transactions made by Whales. Transactions that involve significant amounts of cryptocurrencies that might affect Bitcoin prices are publicly announced on Twitter. To gain a better understanding of the impact of crypto-whales on the crypto market, this study uses data from an advanced blockchain tracker on Twitter with the username @whale_alert. This account provides real-time notifications on significant cryptocurrency transactions and has been found to correlate with high-frequency price jumps in Bitcoin, according to Scaillet et al. [29].

Studies have consistently demonstrated the usefulness of social media platforms such as Twitter in predicting stock or cryptocurrency prices. For instance, Zou et. al. [30] utilized the context embeddings of tweets and an LSTM model to improve Bitcoin price predictions. Lamon et. al. [31] explored the impact of the sentiment analysis of news and social media on the price predictions of Bitcoin and Ethereum. Aharon et. al. [32] investigated the relationship between Twitter-based measures of economic and market uncertainty and the performance of four major cryptocurrencies.

In an exploration of the relationship between Twitter tweets and Bitcoin fluctuations, Singh et. al. [33] utilized the ARIMA model and achieved a notable accuracy of 80%. Similarly, Bouteska et. al. [34] conducted a study to determine the impact of Twitter engagement on the prices and returns of cryptocurrencies. They employed the ARIMAX model, which underscored a strong correlation with Twitter activity, providing invaluable implications for investors and corporate investment managers in terms of crafting investment decisions and trading strategies.

This connection between social media activity and cryptocurrency market trends became even more apparent during the COVID-19 pandemic, a period marked by significant upheavals in the cryptocurrency landscape. Despite the market's volatility—soaring to new heights, plummeting, then recovering— the impact on individual cryptocurrencies varied dramatically [35]. Dipple et. al. [36] employed correlated stochastic differential equations to predict cryptocurrency prices

using social media activity as a crucial variable. As per French [37], Twitterinduced uncertainty became a vital indicator of Bitcoin returns during the pandemic. Specifically, it was reported that Bitcoin and Ethereum were major transmitters of COVID-19 market shocks [35].

Following this thread, several other studies have investigated the relationship between social media and cryptocurrency prices or volatility. For instance, Chen et al. [38] found that social media sentiment can be a useful predictor of bitcoin returns, while Bao and Fang [39] used machine-learning techniques to analyze the impact of social media sentiment on cryptocurrency prices. Similarly, Lou et al. [40] utilized natural language processing techniques to investigate the impact of social media sentiment on cryptocurrency returns, whereas Lee et al. [41] found that the tone of news articles can impact the prices of cryptocurrency. Wu et al. [42] reported a significant causal relationship between Twitter-based uncertainty measures and the prices of various cryptocurrencies including Bitcoin, Ethereum, Litecoin, and Ripple.

In conclusion, these studies provide evidence of the utility of social media and news data in predicting stock and cryptocurrency prices as well as cryptocurrency volatility. These findings demonstrate the importance of considering social media and news sentiments in financial analysis and highlight the potential for future research in this area.

Much of the existing research, like [30] and [31], has emphasized sentiment analysis on Twitter to predict cryptocurrency prices. These studies predominantly focus on general sentiment without directly accounting for the substantial transactions by significant market players, the crypto-whales. Recognizing this oversight, our study pivots to the specialized blockchain tracker on Twitter account @whale_alert. Unlike general cryptocurrency discussions on Twitter, @whale_alert provides real-time notifications of sizable cryptocurrency transactions, which [29] found correlates with high-frequency Bitcoin price jumps. By honing in on @whale_alert notifications, we aim to understand the direct impact of major crypto whale transactions on Bitcoin's supply and demand, offering a distinct and crucial insight into market dynamics. Considering this evidence, we focused on incorporating the tweets by @whale_alert into our predictive model using a Q-learning algorithm.

Data Preparation

In this section, we outline the process of obtaining, preprocessing, and utilizing on-chain data from the Bitcoin blockchain and whale alert tweets to forecast Bitcoin volatility. To gather the necessary data, we employed a combination of APIs and web scraping techniques. On-chain data include the transaction volume, transaction count, and miner revenue. Whale alert tweets provide insights into large transactions that may impact the market. The preprocessing stage involves cleaning and transforming the data to make them suitable for analysis. Overall, we created a dataset consisting of on-chain data and the whale alert tweet data that were generated within two years (from 1st of January 2019 to 1st January 2021). Finally, we used a Q-learning algorithm to analyze the dataset and generate predictions of Bitcoin volatility. Below, we discuss the dataset features and examine how they are collected, followed by an overview of the technical indicators and the process of data preprocessing.

Cryptoquant On-Chain Data. To obtain the on-chain Bitcoin data, we accessed the collected data and analyzed them using CryptoQuant (http://cryptoquant.com). CryptoQuant is a blockchain analytics platform that provides real-time data and insights into the Bitcoin network. It is designed to help users gain a deeper understanding of the underlying forces that drive the price of Bitcoin as well as the behavior of market participants. The platform aggregates on-chain data from the Bitcoin blockchain and provides a range of tools and visualizations to help users analyze and interpret data. Overall, CryptoQuant is a powerful tool for anyone seeking to gain a deeper understanding of the Bitcoin market and make informed predictions about future price movements. The platform provides a wealth of on-chain data and insights along with easy-to-use visualizations that make it accessible to users of all skill levels. From the obtained on-chain data, we extract and focus only on the following data features that we believe can be used as price-affecting indicators:

- **Exchange inflows and outflows:** The inflows and outflows of Bitcoin to and from exchanges can provide important insights into market participants' buying and selling behaviors. By tracking the inflow and outflow of Bitcoin to the exchange, one can gain an understanding of how demand for Bitcoin is changing, which can help predict future price movements.
- **Miner outflows:** The outflow of Bitcoin from miner wallets can provide important insights into the selling behavior of miners, which can affect the future price of Bitcoin. By tracking the outflow of Bitcoin from miners' wallets, one can understand how miners affect the supply of Bitcoin, which can help predict future price movements.
- **Stablecoin inflows:** The inflows of stablecoins to exchanges can provide important insights into the buying behavior of market participants. By tracking the inflow of

stablecoins to exchanges, one can gain an understanding of how the demand for Bitcoin is changing, which can help predict future price movements.

Options market data: Options market data provide important insights into market participants' expectations. By tracking options market data, one can understand how market participants expect the future price of Bitcoin to change, which can help predict future price movements.

Methods and Implementation

This section presents our method for forecasting Bitcoin price volatility using a combination of on-chain data and whale alert tweets. Our approach uses a reinforcement learning (RL) algorithm in which the Bitcoin market serves as the environment. The following subsection provides a brief overview of RL and the proposed RL approach.

RL And Q-Learning. RL is a type of machine learning that addresses decision-making problems and focuses on learning a policy that maximizes the reward signal. The fundamental challenge in price prediction is that it involves learning from a dynamic and stochastic environment in which outcomes are uncertain. RL provides a framework for modeling these environments and learning a policy that optimizes the expected cumulative rewards.

RL is based on the MDP, where MDP is a framework that comprises a set of states (S) and actions (A), a reward function (r), a transition probability function (P), and a discount factor (γ). The transition probability function maps the states and actions to the probability distribution of the subsequent states, whereas the reward function maps the states and actions to the scalar reward. The goal of RL is to learn a policy (π) that maximizes expected discounted returns by mapping states to actions. This policy includes a value function (Vπ(S)) and an action value function (Qπ(s,a)). When the state transition probability is not available, the RL agents must learn the optimal policy through trial and error and exploration. The process of learning a policy that maximizes the expected reward is known as model-free learning.

Q-learning is a well-known modelfree algorithm used to improve prediction models in various areas, including social network research. Q-learning is a simple RL algorithm that provides the current state and determines the best action to be performed. It operates using an off-policy learning mechanism, meaning that it learns through random actions. The algorithm uses a Q-table (Q(s,a)) to store the rewards for each state-action pair. The main objective is to learn the Q function. The values of Q are updated at each iteration, following a three-step process: (1) the agent starts in a state, takes an action, and receives a reward; (2) the next action is selected either by referencing the Qtable and choosing the action with the highest value or by taking a random action; and (3) the Q-values are updated. The core of the algorithm is the Bellman equation, which is used as a simple value-iteration update. This equation uses the weighted average of the old value and the new information to update the Q values [45], [46].

$$Qnew(st\,, at\,) = Q(st\,, at\,) + \theta * [rt + \gamma Q * (st + 1, a') - Q(st\,, at\,)], (1)$$

where θ ($0 < \theta \leq 1$) is the learning rate and γ is a discount factor with $0 \leq \gamma \leq 1$. The value of $Q*$ is the estimate of the optimal future value, which is expressed as:

$$Q* = max\ a'\ Q(st+1, a'). (2)$$

This process continues until st+1 reaches its final or terminal state.

RL and Q-learning algorithms play a crucial role in the prediction of Bitcoin price volatility because they address the decision-making and control issues inherent in price prediction. Volatility prediction is challenging because it requires learning from dynamic and uncertain environments. RL offers a solution to this challenge by providing a framework for modeling the environment and learning a policy that maximizes reward signals. In the context of Bitcoin volatility prediction, the agent can be viewed as an individual prediction of the future price direction to maximize profits. The environment can be modeled as a state space that captures information about the Bitcoin market, such as on-chain and whalealert tweet data. The actions taken by the agent are whether the price will increase, decrease, or hold its value and whether the rewards are positive or negative regarding the action's correctness. Q-learning algorithms are particularly well suited to this problem as they can handle large and continuous state spaces and problems with stochastic dynamics. The state space in the context of Bitcoin price prediction can be extensive and needs to capture a large amount of information about the market and the past behavior of the price. The dynamics of the Bitcoin market are also highly stochastic and influenced by various factors, such as news events, investor sentiment, and regulatory changes. The Q-learning algorithm begins with an initial estimate of the Q-values, which are the expected cumulative rewards obtained by performing a specific action in a given state and following a certain policy. The Q-values are updated using the Bellman equation and eventually converge to the optimal Q-values, which represent the best actions to take in each state to maximize the expected cumulative reward. The optimal Q-values can then be used to derive an optimal policy that maps the state to actions to maximize the expected cumulative reward. This policy can be used to make decisions based on the current state of the Bitcoin market, thereby leading to improved profits.

MDP For Given Task. In this prediction problem, an agent interacts with the Bitcoin market environment and learns to predict future prices based on Q-learning. For this purpose, we define tuple <S, A,R> as follows:

•**State space S:** As stated previously, our dataset is in the form of a table with 1097 rows and 7 columns. Each row represents a single day, and each column represents the corresponding type of information for the Bitcoin data for that day. Hence, the state (st) at time t is represented by an entire row with seven columns. That is, at each time step, the agent receives a 7-dimensional array as its current state.

•**Action space A:** The action (at ∈ A) taken by the agent at time t is defined as a prediction of whether the current Bitcoin price will increase, decrease, or remain the same. In other words, the action space consists of three options represented by A = −1, 0, 1, where -1 represents a decrease in price, 1 represents an increase, and 0 signifies no change.

Reward function r: These rewards are provided to the agent upon reaching a certain level or upon completing a specific action. Rewards serve as a gauge of success. Because the focus is on predicting price volatility rather than the exact price, and the action space consists of three options; a simple reward system was implemented. The agent receives a reward of 100 for each correct prediction and a reward of -100 for each incorrect prediction, i.e., the agent is rewarded for accurate predictions and penalized for inaccurate predictions.

CONCLUSION

In the present research, we have devised a unique approach for predicting Bitcoin price trends by combining on-chain data and tweets from the @whale_alert Twitter account. The latter source, offering real-time information on substantial Bitcoin transactions, has proven to be a valuable resource, frequently indicative of notable market shifts.

We utilized the Q-learning algorithm on this hybrid dataset to develop a model capable of predicting increases, decreases, or stability in Bitcoin prices. The performance of our model was assessed through key metrics such as precision, recall, and the F1 score.

Our approach demonstrated notable effectiveness. In predicting price ’Increases’, our model achieved a precision of 0.71, a recall of 0.89, and an F1-score of 0.789. When forecasting ’No-change’, the model presented a precision of 0.95, a recall of 0.86, and an F1-score of 0.902. In scenarios predicting a ’Decrease’ in price, the model attained a precision of 0.79, a recall of 0.92, and an F1-score of 0.85. This research highlights the potential of using combined on-chain and social media data in future applications within the volatile cryptocurrency market.

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