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Forecast of Bitcoin Prices Based on ARIMA Model

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Abstract: Bitcoin, a pioneering cryptocurrency, has captivated the world with its volatility and price swings. Its price forecasts hold vital importance for investors, policymakers, and technologists. This article delves into the intricate domain of researching and predicting Bitcoin prices, grounded in diverse data exploration and stability assessment. The application of sophisticated predictive models further underscores the analysis, encompassing mathematics, statistics, and AI. Beyond financial gains, these forecasts impact regulatory decisions and technological advancements. This article converges multiple disciplines, bridging finance, technology, and data science to unveil Bitcoin's enigmatic behavior. This paper finds that the ARIMA Model can help predict the price of bitcoin. It's not just about predicting prices; it's about deciphering the potential of blockchain and reshaping our understanding of modern finance in an era of profound technological transformation. So investors should consider bitcoin as a long-term investment. The value of Bitcoin has historically appreciated over time, but short-term price fluctuations are common. Investors should avoid making impulsive decisions based on daily price movements. The second is to use reputable cryptocurrency exchanges and hardware wallets to securely store investors' bitcoins.

Keywords: Bitcoins, ARMA-GRAPH model, crytocurrency, finance, data

1. Introduction

Since its inception in 2009, Bitcoin has carved out a unique path in the financial world, characterized by wild volatility and large price swings. Early analyzes of Bitcoin therefore concluded that it did not meet the economic conditions to be classified as money [1]. This cryptocurrency built on the basis of blockchain technology not only upended the traditional financial system, but also sparked discussions about its potential to revolutionize every aspect of our lives and contribute to technological progress. The history of Bitcoin has been a roller coaster of price volatility, which piqued the interest of investors and the public, because Bitcoin is a speculative asset rather than a currency [1]. In its first few years, cryptocurrencies existed only on the outskirts, and their value remained relatively low. However, the turning point came in 2017, when the price of Bitcoin embarked on an unprecedented upward trajectory. By December of that year, Bitcoin reached an all-time high of around $20,000, attracting the attention of mainstream media and investors around the world. Although, like other asset classes, Bitcoin prices are prone to speculative bubbles [2]. This spectacular rise was short-lived as the cryptocurrency then underwent a correction, underscoring the inherent volatility of the nascent cryptocurrency market. In the years following the 2017 surge, Bitcoin's price has continued to fluctuate wildly, often defying conventional market expectations [3]. Critics argue that this volatility hinders bitcoin's adoption as a stable store of value and reliable medium of exchange. They argue that price volatility hinders bitcoin's ability to function effectively as a currency for day-to-day transactions, as people may be hesitant to use an asset that can change in value dramatically in a short period of time. Conversely, proponents of Bitcoin's volatility argue that this characteristic is a natural byproduct of the cryptocurrency's relative youth and changing market dynamics [4]. They stress that extreme price volatility is likely to subside as adoption, regulatory transparency, and institutional involvement increase. The early stages of any disruptive technology are often fraught with uncertainty, and Bitcoin's journey is no exception.

Beyond price movements, Bitcoin's influence extends to the potential benefits it can bring to society and technology. Proponents argue that the decentralized nature of Bitcoin transactions has the potential to fundamentally reshape the financial system [5]. By running on a decentralized ledger, Bitcoin reduces reliance on traditional financial intermediaries and gives individuals greater control over their financial transactions [6]. In addition, Bitcoin has facilitated innovation in the broader blockchain space [7]. The concept of a decentralized, tamper-proof ledger has inspired the development of many other cryptocurrencies and blockchain projects that go beyond finance. From supply chain management to digital authentication, these projects leverage blockchain technology to create more transparent, efficient, and secure systems. While critics see Bitcoin as a speculative asset, others see it as a hedge against traditional financial instruments or an alternative investment in a rapidly digitized world [8]. Factors such as macroeconomic instability, geopolitical tensions, regulatory developments, and technological advances are all influencing Bitcoin price movements. Analyzing Bitcoin's price trends requires a nuanced approach that takes into account both macroeconomic factors and the dynamics of the cryptocurrency market. Analyzing Bitcoin's price holds pivotal significance across sectors. Investors rely on analyses to guide decisions, employing methodologies like technical, fundamental, and sentiment analysis. Market sentiment, news, and events contribute to its high volatility, while economic instability and geopolitical factors drive its role as a potential safe-haven asset [1]. Bitcoin's price trends reflect technological advancements and adoption rates, affecting discussions about digital currencies' impact on financial systems. Moreover, it informs risk management and portfolio diversification strategies [9]. Beyond traders, policymakers, technologists, and researchers value these analyses for insights into blockchain's broader applications and implications. As the cryptocurrency landscape evolves, understanding Bitcoin's price remains a crucial compass in deciphering the intricate interplay of market forces, innovation, and global economic shifts.

The ARMA model can help identify underlying patterns and trends in Bitcoin price data. They can reveal whether bitcoin prices exhibit autocorrelation (relying on past value) and whether there is a seasonal or cyclical pattern. At the same time, by analyzing historical data, investors can make wise predictions about future price trends, which is very valuable for investors. In general, understanding the statistical nature of Bitcoin price movements through ARMA analysis is helpful for risk management.

The subsequent sections of this paper are organized as follows: Section 2 addresses the data origin, data stability, and the models employed. In Section 3, comprehensive exploration of outcomes from the ARIMA model, along with supplementary analysis on stock return, stock volatility, and market participant conduct, is presented. Subsequently, the study's emphasis, objectives, and significance are discussed. Lastly, Section 5 succinctly restates the ultimate conclusions.

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2. Research Design

2.1. Data Source

Amidst a plethora of data accessible across diverse financial platforms, this study harnessed Bitcoin price data sourced from the reputable investment website [10]. This comprehensive endeavor involved extracting the daily opening and closing prices of Bitcoin, spanning the temporal domain from October 1, 2011, to August 8, 2023. Prior to delving into the research, a preliminary data processing phase was imperative. This preliminary phase encompassed the intricate calculation of Bitcoin's historical pricing trends, an essential precursor to any endeavor seeking to chart future price movements. First, the data needs to be processed to calculate the impact of daily increases in the price of Bitcoin on the volatility of the Bitcoin price. Specifically, the difference between the two days' closing prices is divided by the previous day's closing price to get the earnings of the Bitcoin price, and the data is converted through a formula ln (1 + Bitcoin price), and continue the analysis on a logarithmic scale. Armed with meticulously curated and revised datasets, the analytical prowess of the software tool, Stata, was harnessed. It embarked on a multifaceted journey: not only analyzing the data but also constructing intricate models to unravel underlying trends. This approach paves the way for a comprehensive exploration, unveiling the nuances of Bitcoin's intricate price dynamics and potential future trajectories.

2.2. Weak Stationarity Test

The initial phase involves assessing the stationarity of the data as a preliminary step. Employing the Augmented Dickey-Fuller (ADF) test through Stata, the P-values in Table 1 show that the daily and weekly bitcoin price is close to 0. This statistical significance signifies a compelling outcome. Consequently, there is substantial evidence to reject the hypothesis of a unit root for the variables. In simpler terms, the model constructed based on the raw data is not viable, so the sequence after the difference is stationary.

Table 1: Weak stationarity test.

	t	p
Daily		
Ln price	-1.674	0.7620
1st order difference	-55.544	0.0000
Weekly		
Ln price	-1.514	0.8243
1st order difference	-14.703	0.0000
2nd order difference	-14.405	0.0000

2.3. AutoRegressive Integrated Moving Average (ARIMA) Model

The ARIMA (AutoRegressive Integrated Moving Average) model is a statistical technique used for time series forecasting. It combines autoregressive (AR), differencing (I), and moving average (MA) components to predict future data points based on historical observations. The AR component models the relationship between current and past values, the I component addresses data stationarity, and the MA component considers past prediction errors. The model is defined by three parameters (p, d, q) representing the orders of the AR, I, and MA components. ARIMA is widely used for tasks like financial forecasting and demand prediction. It's a versatile tool for capturing patterns in sequential data over time.

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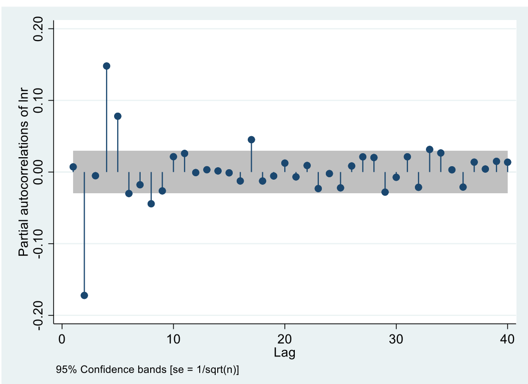
3. Empirical Results and Analysis

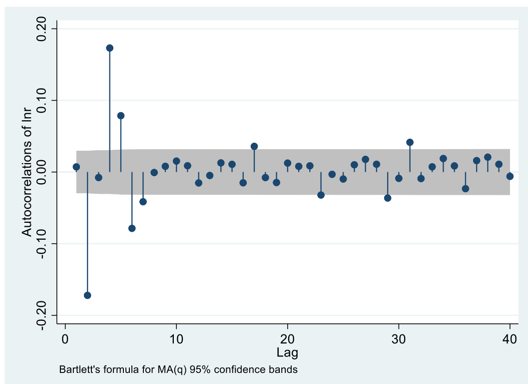
3.1. ARMA (p, q) Identification and Residual Test

Determining the order of an ARIMA model involves choosing appropriate values for its parameters (p, d, q) to ensure that the model fits optimally to a given time series dataset. This process begins by evaluating the variance (d) needed to achieve data stationarity. This is a fundamental requirement of ARIMA modeling because d represents the number of times a time series needs to be differentiated in order for it to become stationary. A stationary time series means that its mean and variance remain constant over time. Subsequently, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the differenced series help to identify significant lags affecting the current observation. Because the 1st order disserence of the weekly PACF graph is difficult to predict, a second derivative is required. These plots guide the order in which the autoregressive (AR) and moving average (MA) components (p and q) are determined. In the daily plot p is 8, d is 1, and q is also 8. To be more specific, p represents the number of past observations considered in the autoregressive (AR) model. Specifically, the ARIMA model will use the data of the previous p time steps to predict the value of the current time step. So when p=8, it means that the model will consider the observations of the previous 8 time steps. d = 1 means that the original time series is only differentiated once to make it stationary. Differencing can help remove seasonal and trend components. q denotes the number of lagged forecast errors considered in the moving average (MA) model. MA models are used to capture the autocorrelation structure of forecast errors. In the case of q=8, it means that the model considers the lagged forecast error for the first 8 time steps. In the figure of weekly, p is also 8, d is 2, and p is 1. p=8 also means that the model will consider the observations of the first 8 time steps. d=2 means you are differencing the original time series twice to make it stationary. This may be because the original data has a strong seasonal or trend component, which needs to be differenced twice to make it stationary. Finally, q=1 means that the model will consider the lagged prediction error of the previous 1 time step. Multiple ARIMA models with different parameter combinations are then created and their accuracy assessed using techniques such as cross-validation or a metric on a validation dataset. The model showing the smallest prediction error on the validation dataset is chosen as the optimal model, and its corresponding p, d, and q values define the order. Once the order is established, an ARIMA model is fitted to the time series data, enabling accurate forecasting of future data points. This meticulous sequence determination process ensures that the ARIMA model effectively captures underlying patterns in the data, enhancing its predictive power.

PACF ACF

Daily





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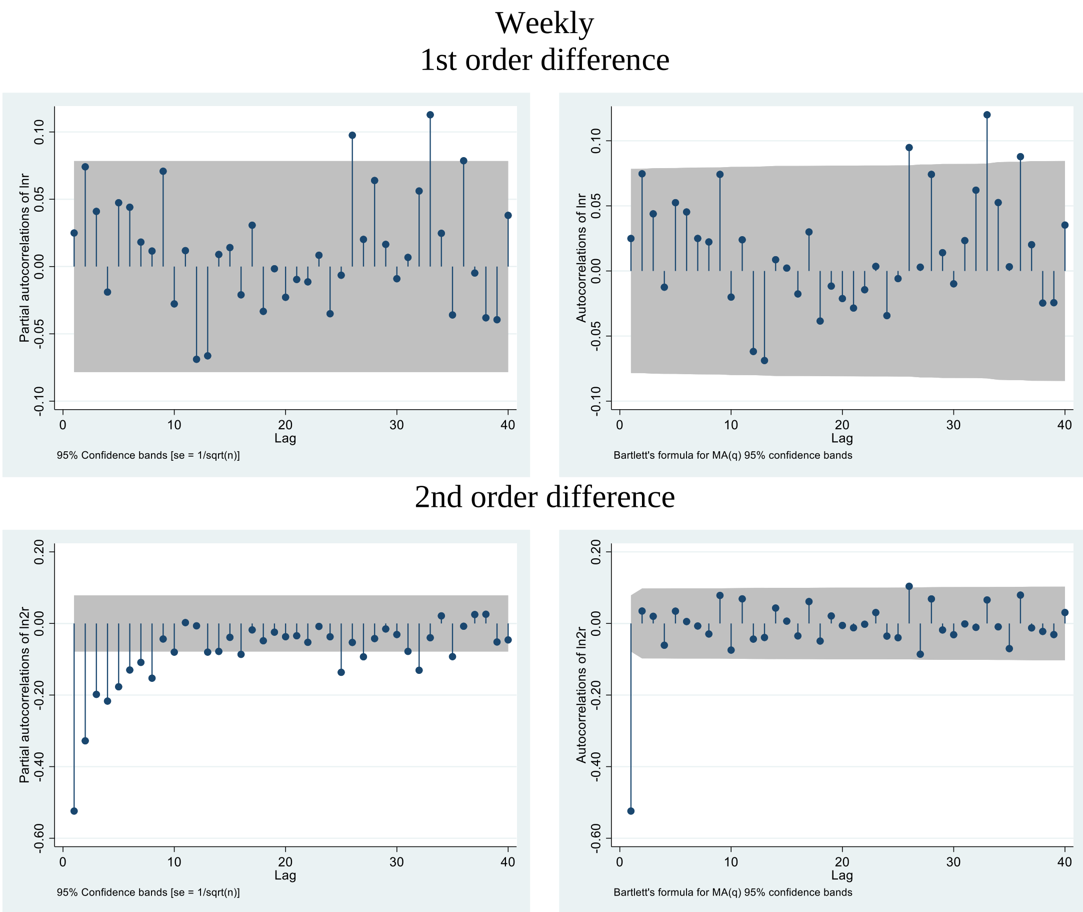

Figure 1: ARMA (p, q) identification.
Photo credit: Original

In the ARIMA model, the use of residual test (residual test) is a commonly used method to evaluate whether the model can well capture the structure in the time series, and whether the residual of the model conforms to some basic assumptions. Residuals are the difference between model predictions and actual observations, and statistical testing of model residuals can help determine whether a model needs further improvement. As shown in Table 2, Portmanteau (Q) statistics is a statistical tool commonly used in residual testing. It is used to check whether the residuals of the model have autocorrelation, that is, whether there is a time correlation between the residuals. The core idea of this test is to assume that the residual sequence is white noise, i.e. does not contain any meaningful time-correlated structure. If the residual series is indeed white noise, then the value of the Portmanteau (Q) statistic should be close to a random variable conforming to the distribution of degrees of freedom. For the daily model and the weekly model, the values of Portmanteau (Q) statistics are 32.9209 and 45.6148 respectively. Their probability is greater than 0.1, which means that the Q statistics are significantly greater than the critical value, then it can be concluded that the residual The sequence is not white noise, there is time correlation, and the model may need to be improved.

Table 2: Residual test.

Model	Portmanteau (Q) statistic	Prob > chi2
Daily-ARIMA(8,1,7)	34.9209	0.6979
Weekly-ARIMA(8,2,1)	45.6148	0.2500

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3.2. Estimated Price

Based on weekly and daily graphs, the price of Bitcoin is likely to rise steadily in the coming month. This forecast is based on technical analysis and trend observations, some of which are as follows (as shown in Figure 2, Figure 3 and Table 3):

First, the weekly Bitcoin price chart shows a positive trend. Over the past few weeks, the price of Bitcoin seems to have experienced a series of upward fluctuations, which indicates that the demand for Bitcoin by market participants is increasing. This continuous upward trend may indicate an increase in buyer confidence and interest in the market, which could drive prices higher.

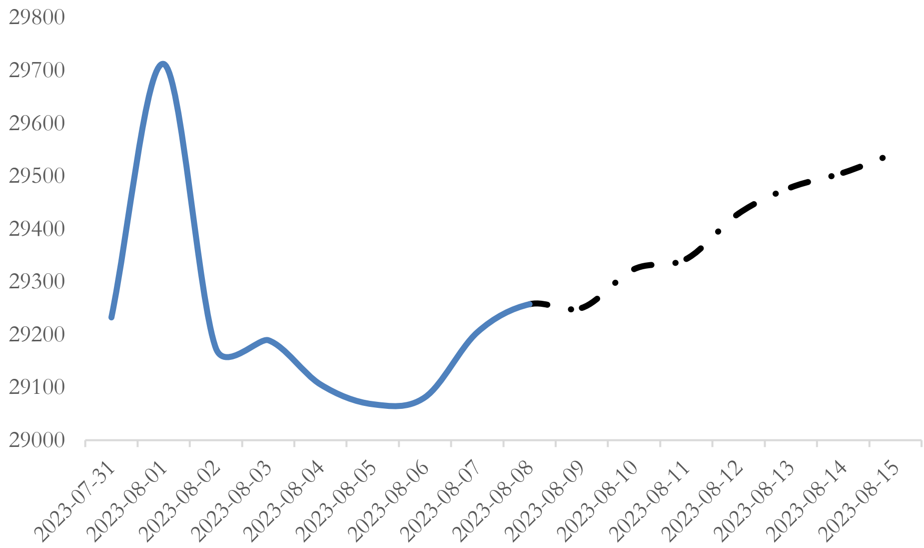

Figure 2: Actual value and fitted value, daily.

Photo credit: Original

Second, the daily price chart supports this view. It can be seen from Figure 2 short-term fluctuations in the price of Bitcoin, but the overall trend shows an upward movement. This volatility may be caused by daily trading activity and news events in the market, but the long-term trend seems to be supported by the continued buy-side.

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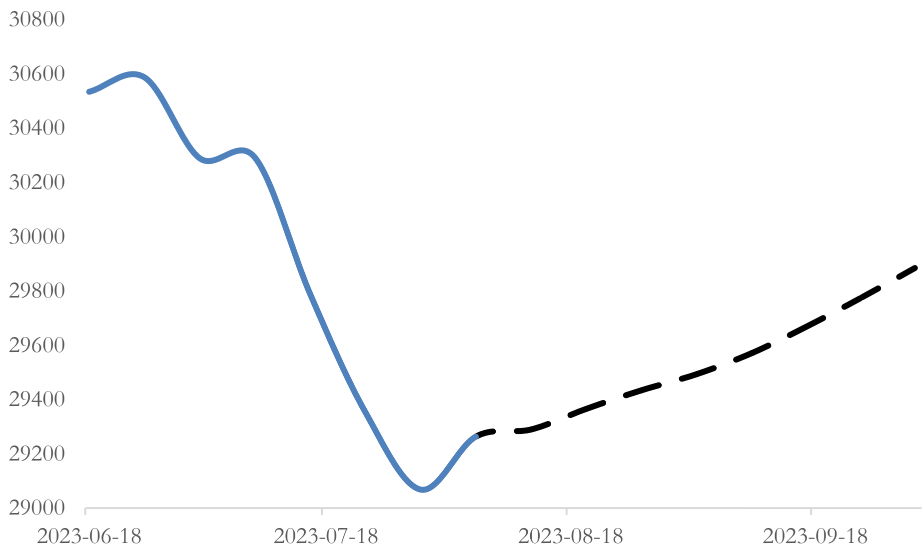

Figure 3: Actual value and fitted value, weekly.
Photo credit: Original

In addition, the fundamentals of the market may also have an impact on the steady rise in the price of Bitcoin in the coming month. Several factors, such as the participation of institutional investors, increased awareness of Bitcoin, and wider adoption of digital assets, could drive the price of bitcoin higher.

Table 3: Prediction.

	Daily		Weekly	
	Date	Price	Date	price
Actual value	2023-07-31	29232.4	2023-06-18	30533.6
	2023-08-01	29712.2	2023-06-25	30586.8
	2023-08-02	29173.7	2023-07-02	30288.8
	2023-08-03	29189.3	2023-07-09	30291.4
	2023-08-04	29105.5	2023-07-16	29788.9
	2023-08-05	29068.1	2023-07-23	29353.5
	2023-08-06	29081.3	2023-07-30	29068.1
	2023-08-07	29204.2	2023-08-06	29263.2
Fitted value	2023-08-08	29257.4	2023-08-13	29289.51
	2023-08-09	29250.45	2023-08-20	29365.41
	2023-08-10	29323.79	2023-08-27	29433.89
	2023-08-11	29343.06	2023-09-03	29493.4

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Table 3: (continued).

	2023-08-12	29429.03	2023-09-10	29571.05
	2023-08-13	29478.42	2023-09-17	29669.67
	2023-08-14	29506.16	2023-09-24	29777.18
	2023-08-15	29543.76	2023-10-01	29890.02

3.3. Discussion

Compared with other studies, this paper focuses on the historical price of bitcoin and makes new predictions about the future price. In terms of analyzing the price of Bitcoin, many studies are similar to this paper, because many studies have adopted methodologies such as VAR model [5], GARCH model [6]. Or use the relevant conversion method to predict the movement of the Bitcoin price. Through the study of this article, technology may indicate patterns and trends of future price movements. For investors who follow the price of bitcoin, understanding the stability of the market and the impact of events on the price of bitcoin is key. They need to use similar methodologies, such as VAR model, GARCH model, etc., to predict the changes in Bitcoin prices and pay close attention to relevant news and information in order to make timely investment strategy adjustments when the market changes.

Nevertheless, the price prediction of Bitcoin has been a topic of much attention and debate in the financial and cryptocurrency communities due to the volatility of the cryptocurrency market and the complex factors that affect its value. Bitcoin has a history of extreme price volatility, characterized by rapid fluctuations in its value. While historical data can provide insight into past price trends, it is not always a reliable indicator of future performance. The factors that have caused price movements in the past do not necessarily repeat in the same way. Market sentiment, including investor psychology, media coverage, and public perception, plays an important role in the formation of Bitcoin's price. Positive news or regulatory developments could push prices higher, while negative news could lead to a sell-off. However, accurately quantifying and predicting emotions is challenging. The cryptocurrency market is relatively small compared to traditional financial markets, making it vulnerable to market manipulation. Whales (individuals or entities that hold large amounts of stock) can influence prices by coordinating buying and selling, making it difficult to accurately predict price movements. Finally, the price of Bitcoin can be affected by external events such as regulatory changes, technological advances, macroeconomic factors, and global financial instability. These factors are often unpredictable and can lead to sudden and significant changes in prices.

4. Conclusion

In short, predicting the price of Bitcoin is a complex task that is influenced by factors such as financial analysis, technical trends, market sentiment, and macroeconomics. The study highlights the complexity of cryptocurrency market forecasts, which are characterized by volatility and regulatory dynamics. While a variety of methods, such as fundamental analysis and technical analysis, provide insights, they acknowledge the unpredictability of markets. Integrating multiple analytics methods, machine learning, and real-time data can improve forecast accuracy, but external events can disrupt trends. Due to the rapid development of the market, flexibility and adaptability are essential. Constant refinement and adaptation, taking into account new variables and technologies, is critical to staying relevant. While data analytics provide valuable insights, due to market volatility, it is also important to exercise caution in your forecasts. Acknowledging the speculative nature of forecasts can guide decision-making. To advance predictive models, researchers should collaborate between academia, industry, and regulators. This has fostered an informed and resilient cryptocurrency market. As the Bitcoin landscape evolves, researchers must embrace change, deepen understanding, and facilitate responsible decision-making in this dynamic space.

For investors looking to use ARIMA models to predict Bitcoin prices, several key recommendations should be considered. First and foremost, it's essential to understand the limitations of the ARIMA model. While it can capture certain trends and cyclical patterns in time series data, it cannot account for all factors influencing Bitcoin prices, such as market sentiment, news events, and regulatory changes. Second, it's advisable to incorporate multiple data sources beyond historical prices, including trading volumes, market capitalization, and market volatility, to enhance model accuracy. Additionally, rigorous model evaluation, including cross-validation, is critical to ensure the model's reliability in predicting new data. Given the high volatility in the Bitcoin market, effective risk management strategies, such as stop-loss and take-profit orders, should be in place to mitigate potential losses. Furthermore, it's crucial to diversify information sources, listening to investment experts, analysts, and researchers, for a comprehensive view of market dynamics. Lastly, investors should define their investment goals and timeframes clearly, recognizing that Bitcoin price prediction may be more suitable for short-term strategies, while long-term investments require consideration of fundamentals and broader market trends. In sum, while ARIMA models can be valuable tools for Bitcoin price prediction, a holistic approach to investment decision-making, encompassing various factors and risk management, is paramount for successful cryptocurrency investments.

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