Exploring a Hybrid Algorithm for Price Volatility Prediction of Bitcoin

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Abstract: In recent years, the Bitcoin investment market has become increasingly popular. We collected existing literature on Bitcoin and found that predictions about the role of Bitcoin in investment portfolios and the volatility of Bitcoin price as well as return have become advanced research topics. This study shows our current work on the prediction of Bitcoin price volatility and proposes an idea for predicting the price volatility. We have designed an experiment that compares different combinations of machine learning algorithms with GARCH-type models, intending to compare the effects of these models in the prediction of Bitcoin time series and finally implement an optimized algorithm.

Keywords: Bitcoin, GARCH, volatility prediction, machine learning

1. INTRODUCTION

Since the advent of Bitcoin, many investors and researchers worldwide have set their sights on cryptocurrencies. Satoshi Nakamoto[1] proposed the design of Bitcoin, and defined Bitcoin as an electronic cash system for point-to-point transmission to financial intermediaries. Though Bitcoin was originally created for disintermediated payments, it had gradually become a financial asset-like item. As the Bitcoin market had rapidly become fascinating, other cryptocurrencies such as Litecoin and Ethereum had also been issued and became new investment targets. But many scholars[2][3][4] believed that Bitcoin is the first and most popular cryptocurrency in the world, so Bitcoin is also the most representative cryptocurrency which can reflect the characteristics of cryptocurrencies. Hence, many existing pieces of research on cryptocurrencies have Bitcoin as their main research object. Glaser et al.[5] 's research found that most Bitcoin holders use this cryptocurrency as a special financial asset rather than a means of payment through empirical methods. It is well known that Bitcoin does not have any assets or government credit issuance as a guarantee, and the demand side of the market was dominated by short-term speculators and follow-up investors. They wanted to keep cryptocurrencies and waited for the price to rise in order to make a profit. By analyzing the correlation between the search results of "Bitcoin" in Google Trends and the price of Bitcoin, Kristoufek[6] found that the price of Bitcoin is positively correlated with the popularity of public opinion.

Although Bitcoin investment is risky, the decentralized nature of Bitcoin and the frequent fluctuations of the investment market make the Bitcoin investment market an excellent "battlefield" for investors with high-risk appetite. More scholars are also trying to learn more about the nature of the cryptocurrencies and the characteristics of the cryptocurrency market. As the amount of Bitcoin in the market is fixed, the supply of Bitcoin is a constant, which is fundamentally different from other centralized currencies. In the traditional financial field, additional currency will affect the relative value of the currency, but this nature does not apply to cryptocurrencies such as Bitcoin. Böhme[7] classified Bitcoin as a kind of virtual currency and defined virtual currency as a kind of digital asset that is created to act as a transaction intermediary using cryptographic methods. Hence, Bitcoin can be regarded as a new type of financial asset because it can be used for both payment and investment.

Existing researches have showed that cryptocurrencies are more volatile than traditional currencies[8] , and

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estimating cryptocurrencies' volatility is necessary. Dyhrber[9] analyzed the volatility of bitcoin return rate and gold price, the exchange rate trend of bitcoin against the U.S. dollar and the pound with the GARCH model, founding that bitcoin has certain similarities with traditional currencies and gold, which can be used as an effective risk management tool in the investment market. The research at this stage comprehensively analyzed the relationship between Bitcoin and its derivatives (e.g. the Bitcoin futures) and other currencies (e.g. USD, EUR, GBP and mainstream currency exchange rates), financial assets (e.g. the gold), investment markets. To some extent, it proves that cryptocurrencies such as Bitcoin have the characteristics of both traditional currencies and financial investment targets. In particular, it has been found that bitcoin has the ability to hedge in investment[10]. These findings support the research on risk management and other aspects.

In our study, the time series models especially the GARCH-type models and machine learning methods will be tested to find a hybrid algorithm which is used to examining the volatility of Bitcoin efficiently.

2. LITERATURE REVIEW

2.1 Bitcoin volatility prediction based on GARCH-type models

As cryptocurrencies becoming popular investment targets, research on the risk control, price prediction, and volatility prediction of cryptocurrencies investment has begun to have very important academic and practical significance. In empirical research on Bitcoin, the prediction of Bitcoin price volatility or return volatility has been a popular topic in recent years. Polasiket et al.[11] found that under the condition of constant supply, Bitcoin investors are more inclined to keep Bitcoins rather than using them for consumption or trade. And it is one of the reasons that the price of Bitcoin is more volatile than traditional currencies[12].Besides, Bitcoin, as a new type of financial asset, has a considerable daily transaction volume and shows obvious fluctuation characteristics in the time series, which is very suitable for using time series analysis methods[13]. The GARCH-type models (Generalized Autoregressive Conditional Heteroscedasticity model) are very classical in time series analysis. Kim W et al.[14] used the Difference-In-Differences model (DID) and the Markov-GARCH model to study the effect of Bitcoin futures trading on the intra-day fluctuation of Bitcoin and found that the introduction of Bitcoin futures will initially stimulate the Bitcoin market volatility but the Bitcoin market will gradually stabilize. Chu[3] used 12 kinds of GARCH models to predict the logarithm of exchange rate returns for seven mainstream cryptocurrencies (obtained based on total value) and found that the IGARCH and GJR-GARCH models fit best. Chu[3] also pointed out that by looking at the intraday fluctuations of cryptocurrencies, it is clear that the prices of cryptocurrencies are volatile, which makes it more suitable for investors with a medium-high risk preference. Katsiampa et al.[15] proposed AR (1)-CGARCH (1,1) model to predict the price return of Bitcoin, which can be useful in risk management and portfolio.

An important premise of GARCH models is that the variance is not constant. Factors such as policy, financial news, etc. may cause differences in prediction accuracy, and the variance of the error term is up to its changes in the previous period, that is, there is autocorrelation. As previous studies show, besides conventional regression analysis, GARCH models also analyze the variance of errors, which makes it ideal for predicting and analyzing volatility.

2.2 Financial prediction based on methods of machine learning

With the increasing application of Artificial Intelligence in financial market research, many researchers have combined machine learning algorithms with econometric models to provide new research methods for financial asset pricing and even related research on cryptocurrencies. Rekabsaz et al.[16] used Support Vector Machines (SVMs) to conduct sentiment analysis on the annual report information of more than 3,000 U.S. stock listed companies. At the same time, the study utilized panel data on U.S. stocks, using the GARCH-type models to analyze the sample stock price volatility. Finally, the feature vectors obtained by SVMs were used to predict the stock price volatility, and a combination of structured and unstructured data analysis was realized, which achieved higher accuracy than the traditional econometric model.

Of course, Bitcoin is also a good object for this type of method. Chen et al.[17] had done a lot of valuable work. Focusing on the high dimensional dataset, Chen used traditional econometric models such as Logit Regression, and machine learning models such as SVMs, Random Forest, Long-Short-Term Memory Neural Network (LSTM), etc., respectively, to make prediction about the daily frequency data and the five-minute price data of Bitcoin. They found that traditional models have better performance on low-frequency data. On high-frequency data, machine learning models, especially SVMs and LSTM, have better results in terms of accuracy. However, Chen's research did not combine time series analysis models, leading to a lack of explanation of changes in the Bitcoin market. McNally[13] suggested that the price prediction of Bitcoin is very similar to other financial assets, especially in time series prediction tasks, such as the prediction of stock transactions and foreign exchange, so deep learning algorithms were used to predict the price of Bitcoin, and compared the experimental results with the results of traditional time series analysis model e.g. ARIMA model. It is found that the accuracy of deep learning prediction is higher than that of the ARIMA model, and the mean square error is greatly reduced. Peng et al.[18], in order to build a non-linear model based on the GARCH (1,1) model, introduced the SVR-GARCH model, based on the Support Vector Regression model (SVR), which perform better than GARCH (1,1) model in the price prediction of 3 kinds of cryptocurrencies.

It can be said that the existing researches have made a lot of contribution to Bitcoin price prediction and return prediction. However, most related researches using hybrid algorithms for prediction simply emphasize the accuracy of the models, without considering the feature engineering. Although Google Trend, Baidu Index, and other indicators have been proven to be applicable to the research on the price and return of Bitcoin, the use of this type of data has not been effectively combined with Bitcoin panel data.

We hope that by comparing different machine learning algorithms or time series analysis models (e.g. SVR-GARCH model[18], LSTM and traditional GARCH-type models, etc.), a better way of predicting the price volatility of Bitcoin in the case of high-dimensional data can be found.

3. METHODOLOGY

This study intends to use the Bitcoin price data from Bitstamp from January 2018 to December 2019 as basic data, and collect Twitter text, Baidu Search Index and Google Trend Index from the Internet as supplements. Figure 1. shows the daily closing price of Bitcoin, and Figure 2. Shows the daily standardized Google Trend Index of Bitcoin.

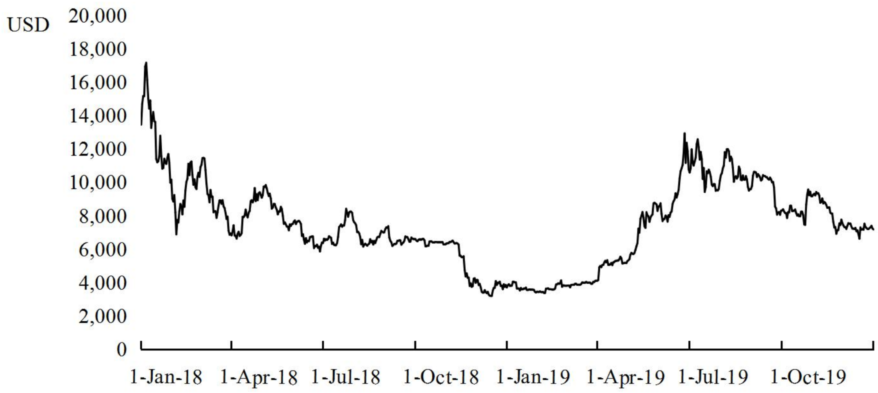

Figure 1. Daily frequency of Bitcoin

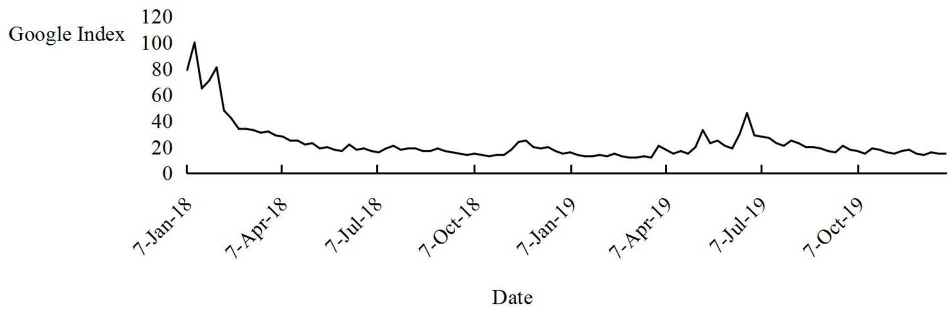

Figure 2. Daily Google Trend Index of Bitcoin

3.1 GARCH-type models

As mentioned before, Peng[18] introduced the SVR-GARCH model to Bitcoin price volatility prediction, the study compared combinations of GARCH-type models (e.g. GARCH (1,1), EGARCH, and GJR-GARCH) and SVR. Chu[3] compared 12 kinds of GARCH models and found that IGARCH (1,1) fits Bitcoin best. We consider using the IGARCH (1,1) model, combined with SVR, to test whether the SVR-IGARCH model outperforms SVR-GARCH model and GARCH (1,1) model.

3.1.1 GARCH (1,1) model

Following Bollerslev[19], the GARCH (1,1) model can be defined as:

$$r_t = \mu + a_t, a_t = \sqrt{h_t}\varepsilon_t, \varepsilon_t \sim N(0,1),$$
$$h_t = \alpha_0 + \alpha_1 \alpha_{t-1}^2 + \beta_1 h_{t-1},$$

where r_t is the return at period t. Let ϵ_t denote the random error term with a zero mean and a variance of one, and h_t is the conditional variance at time t. In the GARCH (1,1) model, the coefficients need to satisfy $\alpha_1, \beta_1 \geq 0$ and $\alpha_0 > 0$, and $\alpha_1 + \beta_1 < 1$ is required to ensure that the fluctuation does not tend to infinity. The distributions of error terms mainly include Normal Distribution, Generalized Error Distribution, and Students 't Distribution.

3.1.2 IGARCH (1,1) model

The IGARCH model is a one-time difference to the GARCH model. With the same sign as GARCH (1,1), the model can be defined as:

$$r_t = \mu + a_t, a_t = \sqrt{h_t}\varepsilon_t, \varepsilon_t \sim D(0,1),$$
$$h_t = \alpha_0 + \alpha_1 \alpha_{t-1}^2 + (1 - \alpha_1) h_{t-1},$$

where $r_t = \log\left(\frac{P_t}{P_{t-1}}\right)$, which represents the return at t, let ϵ_t denote the random error term with a zero mean and a variance of one, and h_t is the conditional variance at t.

3.1.3 SVR-GARCH (1,1) model

The SVR-GARCH model is a combination of Support Vector Regression and GARCH models. It introduces nonlinear components into the GARCH (1,1) model. In essence, it introduces a kernel function into the error term of the GARCH (1,1) model. An empirical study by Chen et al.[21] proves that the SVR-GARCH model performs better in prediction than standard GARCH-type models and fits nonlinear financial data better. Compared with the GARCH (1,1) model, the SVR-GARCH (1,1) model has slightly difference:

$$r_t = f_m(r_{t-1}) + \alpha_t,$$
$$h_t = f_v(h_{t-1}, \epsilon_{t-1}^2),$$

where $f_m(.)$ is the decision function of the SVR mean formula, and $f_v(.)$ is the decision function of the SVR wave equation.

3.2 Machine learning algorithms for Bitcoin prediction

Chen's research[17] trained almost all mainstream algorithms to predict the rise and fall of the Bitcoin price and finally found that SVMs and LSTM achieved the highest accuracy. We plan to replace the role of SVR with other machine learning algorithms for further analyzing the effects of SVMs and LSTM, after comparing SVR-IGARCH and SVR-GARCH.

3.2.1 Support Vector Machines (SVMs)

Support Vector Machines are supervised algorithms. It can transform non-linear problems into quadratic programming problems by mapping samples from the original space to a higher-dimensional space, making the samples linearly separable. As we selected data from January 1, 2018 to December 31, 2019, which is a kind of small size sample in machine learning practice, SVMs may be suitable for our study due to its good performance on small sample data. Support Vector Regression is an example of SVMs used for regression. The difficulty of this algorithm lies in the selection of kernel function in practice. The kernel function plays a decisive role in the quality of feature space, which affects the performance of SVMs. At present, there is no clear method to choose kernel function, and most researchers and practitioners can only determine the choice of kernel function by experience and repeated attempts. The following table lists the commonly used kernel functions[20]:

Table 1. List of common kernel functions

Kernel Functions	Expression	Note
Linear Kernel	$\kappa(\boldsymbol{x}_i,\boldsymbol{x}_j) = \boldsymbol{x}_i^{\mathrm{T}}\boldsymbol{x}_j$	
Polynomial Kernel	$\kappa(\boldsymbol{x}_i,\boldsymbol{x}_j) = (\boldsymbol{x}_i^{\mathrm{T}}\boldsymbol{x}_j)^d$	d is the polynomial degree
Gaussian Kernel	$\kappa(x_i,x_j) = \exp\left(-\frac{\parallel x_i - x_j \parallel^2}{2\sigma^2}\right)$	σ is the bandwidth of the Gaussian kernel
Sigmoid Kernel	$\kappa(\boldsymbol{x}_i,\boldsymbol{x}_j) = \tanh(\beta\boldsymbol{x}_i^{\mathrm{T}}\boldsymbol{x}_j + \theta)$	tanh is the hyperbolic tangent function

3.2.2 Long-Short-Term Memory Neural Network (LSTM)

LSTM is a kind of deep learning neural network. The LSTM model stores information by structures named “cells”. Compared with Recurrent Neural Network, LSTM is special in that there are three special structures: Input Gate, Forget Gate, and Output Gate[22]. Through these three “gates”, the LSTM can control the information to circulate within the model, thereby solving the gradient disappearance problem. The LSTM model can be expressed as in [22]:

$$X = \begin{bmatrix} x_t \\ h_{t-1} \end{bmatrix},$$
$$f_t = \delta\left(W_f \cdot [h_{t-1},x_t] + b_f\right),$$
$$i_t = \delta(W_i \cdot [h_{t-1},x_t] + b_i),$$
$$o_t = \delta(W_o \cdot [h_{t-1},x_t] + b_o),$$
$$\widetilde{C}_t = tanh\,(W_c \cdot [h_{t-1},x_t] + b_c),$$
$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t,$$
$$h_t = o_t * tanh\,(C_t),$$

x_t is the input information at time t, h_t denotes the hidden layer at time t, W_f,W_I,W_o,W_c is the weight matrix of LSTM, b_f,b_I,b_o,b_c are the bias terms of the model, and δ is the activation function. Usually, neural network models use the Sigmoid function as the activation function, which * means dot multiplication. The function Sigmoid is used to convert the input information into values from 0 to 1, where 1 represents all reserved information and 0 represents all forgotten information. The specific form is as follows:

$$\delta(x) = \frac{1}{1+e^{-x}}$$

4. FUTURE WORK

4.1 Feature selection

Feature selection is a very important part of the practice in machine learning. For many machine learning algorithms e.g. SVMs, the quality of the feature space directly affects the training result of the model. Many studies on bitcoin price or return forecasting focus on how to improve the accuracy of the model by ignoring fine-grained processing of features. Part of the reason is that most of the relevant studies use data from Bitcoin panel data, but there is very little practice of adding search indexes or even financial text data to the panel data. Table 2. shows the features we intend to select, in addition to the features from panel data.

Table 2. The features planned to use

Number	Feature	Description[一]	Unit
1	Blockchain Size	Blockchain is the record of Bitcoin transactions which is public to all Bitcoin users.	GB
2	Total Amount of Blocks	Blocks are records in the blockchain that contain and confirm many waiting transactions.	Ten thousand
3	Google Trend Search Index	The daily standardized search volume of "Bitcoin" on Google.[6]	
4	Baidu Search Index	The daily standardized search volume of "Bitcoin" on Baidu.com.[17]	
5	Twitter Sentiment	The result of sentiment analysis of Twitter text. [23]	

4.2 Experimental steps

Whether the combination of machine learning / deep learning algorithms and GARCH-type models can achieve good results in Bitcoin price prediction is the question we want to explore. First, we will compare the mature SVR-GARCH (1,1) model with the SVR-IGARCH (1,1) model to judge whether there is any possibility of improvement in the combination of SVMs and GARCH-type models. Then, we will replace SVR with other machine learning algorithms, and compare the newly improved model with the SVR-GARCH model and LSTM model, and finally find a way to achieve the highest accuracy under given conditions. Figure 3. shows the workflow we have designed.

[一] From: https://bitcoin.org/en/vocabulary#bitcoin

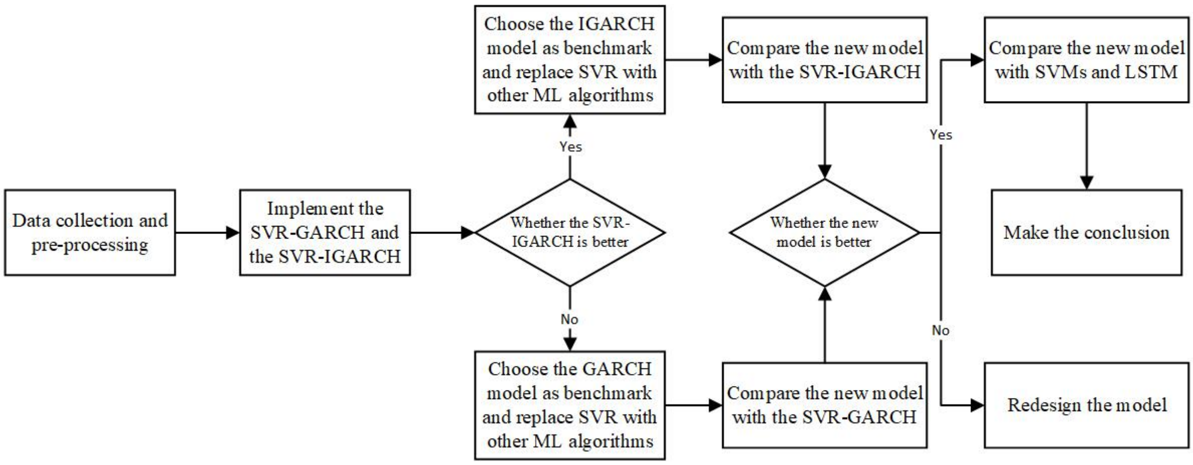

Figure 3. The workflow of the experiment

The core idea of this study is to test and improve the existing Bitcoin volatility prediction methods. Existing studies have fully discussed the factors that affect the price of Bitcoin, and the difficulty we met is that it is difficult for us to obtain complete data of these factors, especially high-frequency data. Furthermore, we are not sure if there is a more suitable mathematical model as a benchmark. Hence, besides the experiment, we will further our study on related theoretical frameworks and mathematical models.

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