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Machine learning model for Bitcoin exchange rate prediction using economic and technology determinants

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ABSTRACT

In recent years, Bitcoin exchange rate prediction has attracted the interest of researchers and investors. Some studies have used traditional statistical and econometric methods to understand the economic and technology determinants of Bitcoin, few have considered the development of predictive models using these determinants. In this study, we developed a two-stage approach for exploring whether the information hidden in economic and technology determinants can accurately predict the Bitcoin exchange rate. In the first stage, two nonlinear feature selection methods comprising an artificial neural network and random forest are used to reduce the subset of potential predictors by measuring the importance of economic and technology factors. In the second stage, the potential predictors are integrated into long short-term memory (LSTM) to predict the Bitcoin exchange rate regardless of the previous exchange rate. Our results showed that by using the economic and technology determinants, LSTM could achieve better predictive performance than the autoregressive integrated moving average, support vector regression, adaptive network fuzzy inference system, and LSTM methods, which all use the previous exchange rate. Thus, information obtained from economic and technology determinants is more important for predicting the Bitcoin exchange rate than the previous exchange rate.

1. Introduction

The cryptocurrency market has boomed in the past decade. Compared with traditional currencies, the biggest innovation of cryptocurrencies is the establishment of a new distributed payment system based on cryptographic protocols, which ensures anonymous, inexpensive, and rapid peer-to-peer transactions. Bitcoin is the first successful example of a decentralized cryptocurrency. Bitcoin does not have a centralized issuer, but instead it is generated by calculations on the network nodes. Bitcoin is distributed worldwide and it can be bought and sold on any computer connected to the Internet. In addition, cryptography-based design allows Bitcoin to be transferred or paid only by the actual owner, which also ensures the anonymity of the currency ownership and circulating transactions. According to the "coinmarketcap" website (at https://coinmarketcap.com; accessed on August 1, 2018), Bitcoin accounted for more than 48% of the market value of cryptocurrency. At present, Bitcoin remains the leader in the cryptocurrency market.

Due to the innovation and market position of Bitcoin, many studies have investigated the Bitcoin exchange rate prediction problem. The different Bitcoin exchange rate prediction approaches can be divided into statistical models and artificial intelligence (AI) models (Wang, Wang, Zhang, & Guo, 2012). Statistical models such as the autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroskedasticity, and exponentially weighted moving-average models are the most commonly used analytical tools (Baur, Dimpfl, & Kuck, 2018; Demir, Gozgor, Chi, & Vigne, 2018; Dyhrberg, 2015; Kancs, 2014). These approaches have

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been used widely but they can only deal with linear problems and the variables must follow a normal distribution (Cheng, Chen, & Wei, 2010). To overcome these limitations, AI models such as artificial neural networks (ANNs), Bayesian neural networks, and support vector regression (SVR) have been utilized to predict the price of Bitcoin (Jang & Lee, 2018; Kristjanpoller & Minutolo, 2018; Mcnally, Roche, & Caton, 2018; Peng, Albuquerque, de Sá, Padula, & Montenegro, 2018; Zbikowski, 2016). These AI approaches allow the extraction of hidden, novel patterns and extraordinary information from large data sets without requiring any prior knowledge about the data.

The current research on Bitcoin exchange rate prediction used the previous exchange rates as predictors. However, the sequence for Bitcoin exhibits complex and highly unstable behavior. Thus, it is necessary to consider various determinants of the Bitcoin exchange rate (Kristoufek, 2013). The determinants of the Bitcoin exchange rate have been explored using econometric techniques such as vector autoregressive (VAR), ordinary least squares (OLS), and quantile regression (QR) in order to understand the effects of economic and technology determinants on the Bitcoin exchange rate. Kristoufek (2013) claimed that there is a correlation between the Bitcoin exchange rate and search queries on Google Trends and Wikipedia. Polasik, Piotrowska, Wisniewski, Kotkowski, and Lightfoot (2015) found that the Bitcoin exchange rate depends on its overall popularity, media sentiment, and the total number of transactions. Yang and Kim (2015) found that a particular complexity measure for the Bitcoin transaction network flow is significantly correlated with the Bitcoin market return and volatility. Dyhrberg (2015) indicated that there are several similarities between gold and the US dollar. Xin and Chong (2016) estimated that the factors that effect Bitcoin will change from both a long-term and short-term perspective. Balcilar, Bouri, Gupta, and Roubaud (2017) concluded that the volume of Bitcoin transactions can predict the returns, but it cannot help to predict the volatility of the returns. Baur et al. (2018) extended the research conducted by Dyhrberg (2015) and showed that Bitcoin exhibits different return, volatility, and correlation characteristics compared with other assets, including gold and the US dollar. Wei, Wang, Xiao, and Shen (2018) proposed that the Bitcoin exchange rate has strong cross-correlations with the number of transactions and transaction fees. In general, recent research has focused mainly on the effects of various determinants on the Bitcoin exchange rate, rather than the predictive or classification capacity of a model. However, it should be noted that although good prediction results can be obtained by considering several determinants of the Bitcoin exchange rate (Brandvold, Molnár, Vagstad, & Valstad, 2015; Demir et al., 2018; Kristoufek, 2014), many previous studies were based on the following: (a) only considering the linear relationship between Bitcoin and relevant factors, although including these variables might lead to worse predictions because their effects may be nonlinear; (b) using both determinants and the previous exchange rate as predictors, and thus it is unknown whether these factors can predict the future exchange rate; and (c) only investigating the Bitcoin exchange rate in a certain period, and thus it is unclear whether the results cover all possible periods. Therefore, in the present study, we investigated whether the information hidden in economic and technology determinants can accurately predict the Bitcoin exchange rate.

The main contributions of this paper are summarized as follows.

- We used two machine learning methods, comprising ANN and random forest (RF), to reduce the subset of potential predictors by measuring the importance of economic and technology factors.
- We integrated potential predictors into the long short-term memory (LSTM) to obtain predictions and compared its performance with four models that use the previous exchange rate, i.e., ANFIS, SVR, ARIMA, and LSTM, in order to verify the validity of the determinants.

The remainder of this paper is organized as follows. In Section 2, we describe the data used in this study. In Section 3, we explain the proposed method. In Section 4, we present our analyses and discuss the results. Finally, in Section 5, we give our conclusions.

2. Data preparation

The Bitcoin exchange rate is the output target of all the predictive models considered in this study. Bitcoin exchange rate data were obtained from: https://bitcoincharts.com/markets/. As mentioned by Xin and Chong (2016), two categories, namely economic factors and technology factors, affect the changes in the Bitcoin exchange rate.

2.1. Technology category

(1) Blockchain information

The biggest difference between Bitcoin and traditional currencies is that the Bitcoin market builds trust through a blockchain. In this study, we obtained blockchain information from https://blockchain.info/. Moreover, the following blockchain factors need to be considered, as follows.

Block size (MB): the size of the data in the blockchain network containing the permanently recorded data.

Confirmation time: the median time required to complete a decentralized transaction and add it to the blockchain for successful validation.

Difficulty: the difficulty of successfully mining data blocks in transaction information.

Hash rate: a measure of the Bitcoin mining network processing capability.

Mining profitability: total value of the coin-base block rewards and transaction fees paid to miners.

Average transaction fee: the average handling fee for all transactions that occur within a day.

Average transaction value: the average value acquired by all transactions occurring within a day.

Transaction volume: the number of transactions concluded for Bitcoin buyers and sellers.

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Market capitalization: the value calculated by multiplying the price by the circulating supply.

(2) Public attention

Public attention measures such as Wikipedia views and Google searches are important for predicting the Bitcoin exchange rate (Dastgir, Demir, Downing, Gozgor, & Chi, 2018; Polasik et al., 2015; Zhang, Wang, Li, & Shen, 2018). In this study, we used Google Trends and Twitter tweets as measures of public attention. Both factors reflect public attention but they have subtle differences. Google Trends indicates the public's intention to learn about Bitcoin, whereas tweets can represent the public's intention to discuss Bitcoin. Moreover, we used "Bitcoin" (case insensitive) as a keyword to capture the historical search volume from Google Trends (https://trends.google.com/trends/) and to obtain Twitter data (from https://bitinfocharts.com/).

2.2. Economic category

(1) Macroeconomic indicators

It is widely believed that exchange rates, commodities, and global macroeconomic factors will affect emerging economies (Gospodinov & Jamali, 2015; Kandil & Mirzaie, 2002; Mensi, Beljid, Boubaker, & Managi, 2013). In particular, Gajardo, Kristjanpoller, and Minutolo (2018) and Laboissiere, Fernandes, and Lage (2015) found that macroeconomic indicators affect Bitcoin prices over the long term. In this study, we considered several factors comprising the FTSE100, DOW30, VIX, SSE, crude oil price, gold price, S&P500, and NASDAQ.

(2) Global currency ratio (USD)

The similarities between Bitcoin and traditional currencies have been studied by many researchers (Dyhrberg, 2015; Jang & Lee, 2018; Kristjanpoller & Minutolo, 2018). In this study, we take into account the exchange rate between global monetary markets. In particular, we used the exchange rates between major fiat currencies (CHF, EUR, GBP, JPY, and CNY) and the US dollar. Relevant public market data were obtained using the Yahoo YQL Finance API.

Technology and economic factors related to the Bitcoin exchange rate are summarized in Table 1.

3. Methodology

The following research questions were addressed to explore whether the information hidden in economic and technology determinants can accurately predict the Bitcoin exchange rate.

- Q1: Can economic and technology determinants provide higher predictive performance?
- Q2: If the answer to Q1 is "yes," how do the determinants of the Bitcoin exchange rate change over time?

To address these questions, we conducted a two-stage experiment in four periods, as shown in Fig. 1. In stage I, we used two machine learning methods, ANN and RF, to identify economic and technology factors related to the Bitcoin exchange rate, where they formed a subset of potential predictors. In stage II, the potential predictors were fed into the LSTM to predict the Bitcoin exchange rate, regardless of the previous exchange rate. In addition, four models, i.e., ARIMA, SVR, ANFIS, and LSTM, were employed to make predictions based on the previous exchange rate. Moreover, the root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and directional accuracy (DA) were used to compare the predictive performance of the models. Obtaining better performance with the LSTM using the economic and technology predictors would suggest that the information hidden in the economic and technology determinants is more important than the previous price.

3.1. Data preprocessing

(1) Data cleaning

The data used in this study were collected through APIs and websites, so some values were missing or meaningless. Therefore, the statistical average was calculated as an observation when appropriate to replace missing data; otherwise, the corresponding date of the missing value was removed from the data set. As suggested by Serneels, De, and Van Espen (2006), we used the space symbol procedure to delete the corresponding data point for outliers.

(2) Data division

We investigated four important periods for Bitcoin. The first period was from August 1, 2011 to December 31, 2013. During this period, Mt. Gox was the largest Bitcoin exchange operator and the Bitcoin exchange rate exceeded 1 ounce of gold. The second period was from August 1, 2013 to December 31, 2014. During this period, the three major Bitcoin exchange operators, BitStamp, BTCe, and BiFinex, dominated Bitcoin transactions. The third period was from July 1, 2014 to December 31, 2017. During this period, dozens of Bitcoin exchanges operated around the world and the amount of Bitcoin transactions surged in most countries and regions. The fourth period was from July 1, 2015 to July 31, 2018. During this period, the Bitcoin exchange rate was about to break through \$20,000 but it suddenly dropped below \$4500. Dividing the empirical analysis into these four periods allowed us to examine how the determinants of the Bitcoin exchange rate changed over time.

In addition, the division of the training and test sets was an important step for forecasting. We used the data from the last 2 months as the test set and all the remainder as the training set.

(3) Data transformation

The model used in this study requires a feature scaling process to avoid attributes with a larger range of values governing a smaller range of attributes (Rezakazemi, Ghafarinazari, Shirazian, & Khoshsima, 2013). Thus, we used a standardized method to scale the input variables. The specific formula is expressed as follows:

$$X_n = \frac{X - X_{min}}{X_{max} - X_{min}}, \tag{1}$$

where X_{min}, X_{max}, and X_n are the minimum, maximum, and normalized values of the sample data, respectively. Fig. 2 shows the normalized historical data for the Bitcoin exchange rate, economic factors, and technology factors.

Table 1
Technology and economic factors related to Bitcoin.

Category		Factor
Technology	Blockchain information	Block size, confirmation time, average transaction value, hashrate, mining profitability, average transaction fee, difficulty, transaction volume, market capitalization
	Public attention	Tweets, Google Trends
Economic	Macroeconomic indicators	FTSE100, DOW30, VIX, SSE, crude oil price, gold price, S&P500, NASDAQ
	Global currency ratio	CHF, EUR, GBP, JPY, CNY

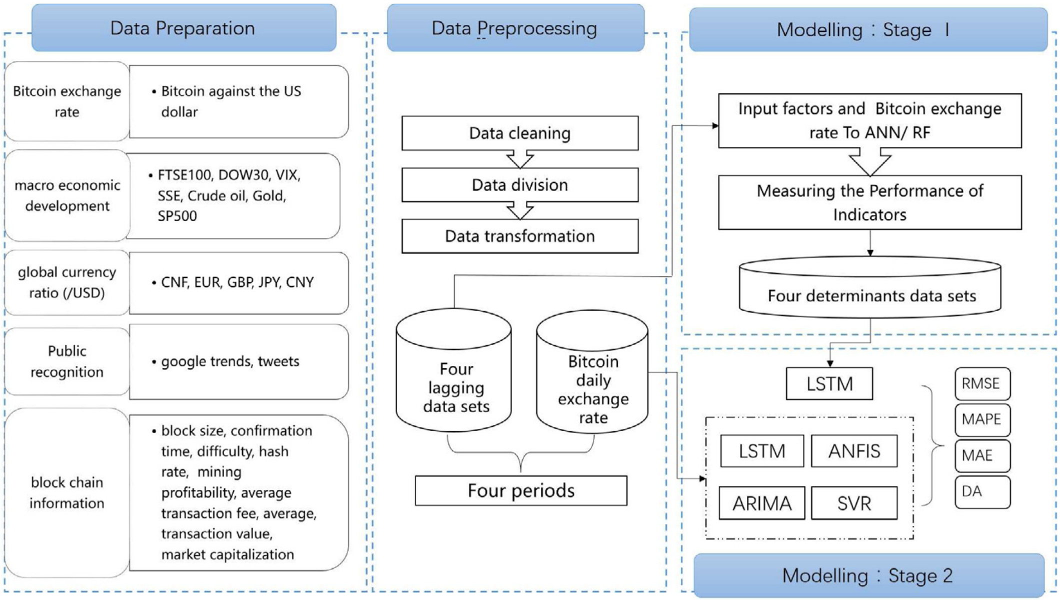


Fig. 1. Two-stage model employed in this study.

3.2. Modeling: Stage I

The economic and technology factors selected in this study were mainly obtained from previous statistical analyses. Integrating them into AI models may result in worse predictive performance. Therefore, in Stage I, we employed feature selection methods to determine the factors with the greatest predictive value, before eliminating redundant factors. Thus, the first stage was divided into the following three steps. In the first step, two machine learning models, RF and ANN, were used. Previous studies have demonstrated that these models obtain good feature selectivity (Enke & Thawornwong, 2005; Tsai & Hsiao, 2011). Next, the importance of different factors was measured using the sensitivity analysis method (Dag, Oztekin, Yucel, Bulur, & Megahed, 2016). The importance values of variables measured using RF and ANN were normalized to [0,1]. In the third step, as pointed out by Tsai and Hsiao (2011), better predictive performance can be obtained by combining multiple feature selection methods rather than using a single method. Therefore, in this study, combinations of unrepresentative variables were filtered with a crossover strategy and the final candidate feature set was generated for stage II. The caret package implemented in the R statistical language was used to develop the ANN and RF models (see Kuhn (2015)).

3.2.1. Random forest

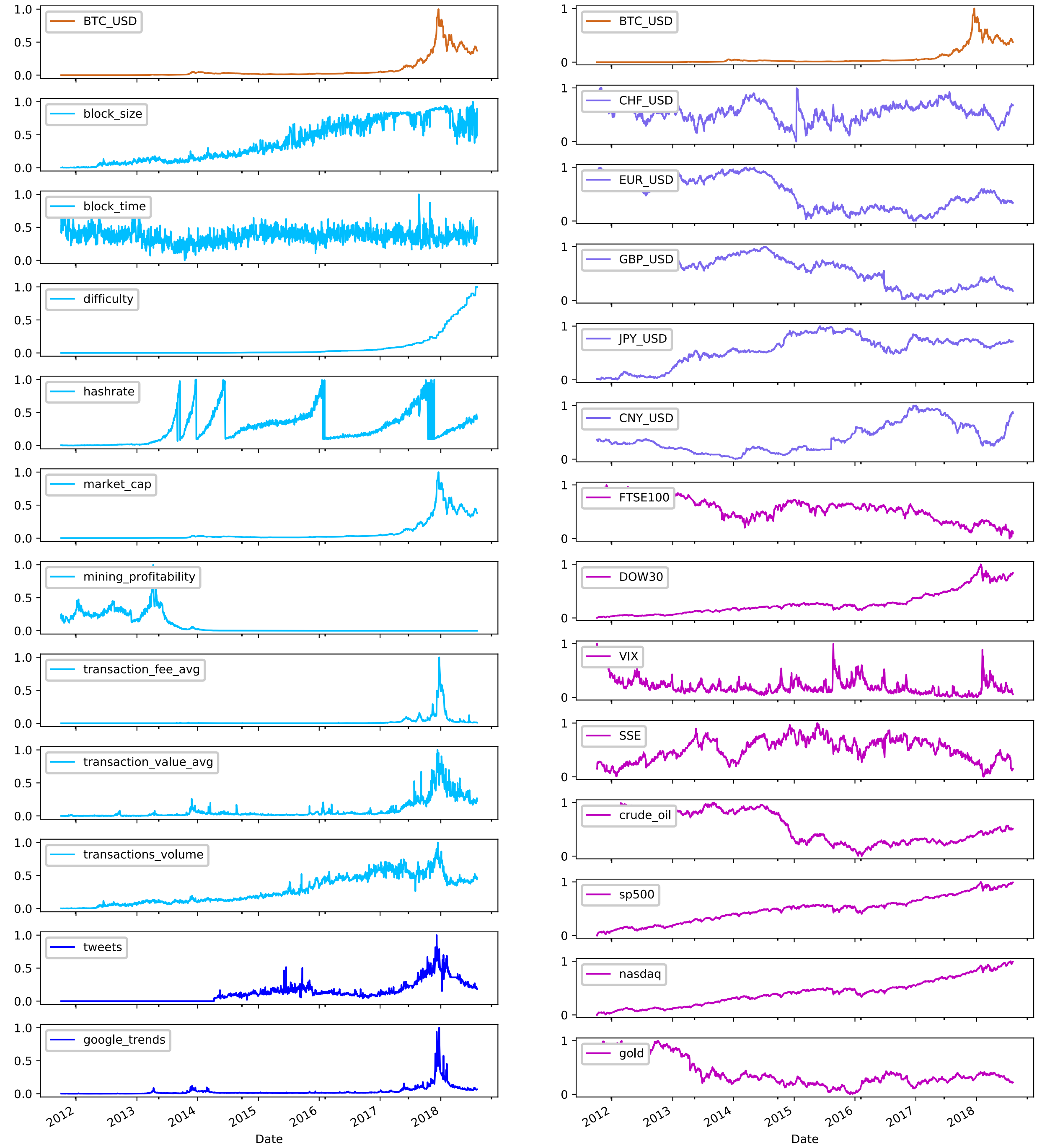
RF is an ensemble machine learning method that uses bootstrap and random node splitting techniques to build multiple decision trees and obtain the final classification results by voting. Compared with a single regression tree, RF is robust to noisy data and missing values, and it has the capacity to analyze complex interactive classification features (Breiman, 2001; Svetnik et al., 2003). In RF, the importance of factor x can be calculated as follows (Lahouar & Slama, 2017).

(i) For each decision tree in RF, n out-of-bag data are used to calculate the out-of-bag error (OOBE), which is denoted as OOBE1. The OOBE is expressed as follows:

$$OOBE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i), \tag{2}$$

where Y_i is the observed value, $\hat{Y}_i$ is the estimated value, and n is the number of forecast periods.

(ii) Randomly add noise interference to factor x in the out-of-bag data and calculate the OOBE again, which is denoted as OOBE2.



(a) Bitcoin exchange rate and technology factors.

(b) Bitcoin exchange rate and economic factors.

Fig. 2. Normalized historical data for the Bitcoin exchange rate, economic factors, and technology factors.

(iii) Suppose that there are N trees in the RF, then the importance of factor x is calculated as follows:

$$I(x) = \frac{1}{N}\sum_{i=1}^{N}(OOBE2 - OOBE1). \tag{3}$$

Further details of the RF method can be found in Cutler, Cutler, and Stevens (2004). In this study, we used 500 trees for the RF implementation.

3.2.2. Artificial neural network

ANNs are used widely in various computational data analysis problems, including classification, regression, and

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pattern recognition. ANNs comprise input layers, implicit layers, and output layers, and each layer consists of some neurons, also called processing elements (PEs). Also ANN can be used to measure the importance of input factor x by measuring the change of mean square error (COE) when the corresponding input is deleted from the network (Xu, Wong, & Chin, 2013). COE is defined as follows:

$$COE = I(x) = MSE2 - MSE1, \tag{4}$$

where

$$MSE = \frac{1}{P}\sum_{p=1}^{P}(Y_i - \hat{Y}_i)^2, \tag{5}$$

and $MSE1$ and $MSE2$ represent the mean square error with and without x, respectively.

For an introduction to ANNs, please refer to the studies by Elhewy, Mesbahi, and Pu (2006) and Gomes and Awruch (2004). In the present study, we used a multi-layer feed-forward neural network structure trained by back-propagation.

3.3. Modeling: Stage II

In this stage, we assumed that the important determinants can provide higher predictive performance in different periods. To evaluate this hypothesis, we incorporated the selected predictors into the LSTM to predict the Bitcoin exchange rate. In addition, four prediction models, i.e., ARIMA, SVR, ANFIS, and LSTM, were used to predict the Bitcoin exchange rate based on previous exchange rates. Moreover, we used four metrics, i.e., MAPE, MAE, RMSE, and DA, to measure the performance of the different models.

3.3.1. Long short-term memory

The LSTM proposed by Hochreiter and Schmidhuber (1997) is the most commonly used model in recursive neural networks (RNNs). The LSTM can obtain better time series predictions because it is difficult to adapt many classical linear methods to multivariate or multi-input prediction problems. Compared with RNNs, the LSTM is characterized by the addition of memory cells for information processing. The structure of a memory cell is illustrated in Fig. 3.

As shown in Fig. 3, at every timestep t, each of the memory cells has three gates, which maintain and adjust their cell state s_t: a forget gate (f_t), an input gate (i_t), and an output gate (o_t). Each gate serves a different purpose, as follows.

Input gate i_t controls the input information flowing into the memory cell, where

$$i_t = \sigma(W_{i,x}x_t + W_{i,h}h_{t-1} + b_i). \tag{6}$$

Forget gate f_t controls the forgetting of information in the cell, where

$$f_t = \sigma(W_{f,x}x_t + W_{f,h}h_{t-1} + b_f). \tag{7}$$

Output gate o_t controls the output information flowing out of the cell, where

$$o_t = \sigma(W_{o,x}x_t + W_{o,h}h_{t-1} + b_o). \tag{8}$$

The input features are calculated by input x_t and the previous hidden state h_{t-1} by a tanh function, as follows:

$$\tilde{s_t} = \tanh(W_{\tilde{s_t},x}x_t + W_{\tilde{s_t},h}h_{t-1} + b_{\tilde{s_t}}). \tag{9}$$

In Eqs. (6)–(9), $W_{i,x}$, $W_{i,h}$, $W_{f,x}$, $W_{f,h}$, $W_{o,x}$, $W_{o,h}$, $W_{\tilde{s_t},x}$, and $W_{\tilde{s_t},h}$ are weight matrices, b_i, b_f, b_0, and $b_{\tilde{s_t}}$ are bias vectors, h_{t-1} is the current input, s_t is the output of the LSTM at the previous time $t-1$, and $\sigma()$ is the sigmoid activation function.

Furthermore, the cell state s_t is calculated as:

$$s_t = f_t \circ s_{t-1} + i_t \circ \tilde{s_t}. \tag{10}$$

The output of the LSTM at the time t is then derived as:

$$h_t = o_t \circ \tan(s_t). \tag{11}$$

where $\circ$ denotes the Hadamard product.

Finally, we project the output h_t to the predicted output $\tilde{y_t}$ as:

$$\tilde{y_t} = W_t h_t, \tag{12}$$

where W_t is a projection matrix for reducing the dimension of h_t.

Due to the relatively small sample size, we used a simple LSTM structure that included an input layer, hidden layer, and output layer. In addition, we applied dropout regularization within the recurrent layer to reduce the risk of overfitting and to utilize early stopping to dynamically derive the number of epochs for training during each study period. The LSTM was implemented using the "keras" package in Python.

3.3.2. Autoregressive integrated moving average

The ARIMA model is a classical statistical time series model. This model is normally expressed as ARIMA (p,d,q), where p is the number of autoregressive terms, d is the number of non-seasonal differences, and q is the number of lag prediction errors present therein. Further details of the ARIMA model were provided by Patle et al. (2015). In this study, we used the "statsmodel" package in Python to fit the model and the Akaike Information Criterion (AIC) introduced by Bozdogan (1987) was used to select the parameters of the ARIMA model.

3.3.3. Support vector regression

SVR is a powerful AI model that has been successfully applied in many fields for time series prediction such as traffic flow prediction (Castro-Neto, Jeong, Jeong, & Han, 2009) and financial time series forecasting (Guo et al., 2018). For further discussion of SVR, see Brereton and Lloyd (2010). Note that SVR makes use of kernels to increase the dimensionality of the data, thereby separating them in a linear manner. Therefore, in this paper, we used the radial basis function as the kernel function because of its capabilities and simple implementation (Huang, Chuang, Wu, & Lai, 2010). SVR was implemented using the "sklearn" package in Python.

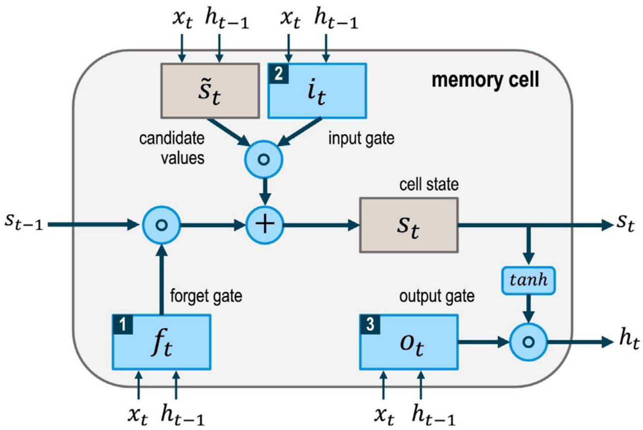

Fig. 3. Memory cell used by the LSTM.

3.3.4. Adaptive network fuzzy inference system (ANFIS)

ANFIS proposed by Jang (1993) is a very successful method for combining ANNs with fuzzy inference systems. ANFIS has been applied successfully in many fields, such as data classification, decision analysis, expert systems, and computer vision (Chang & Chang, 2006). The use of fuzzy logic in networks is achieved with a membership function and fuzzy numbers are used for the whole network. For further discussion of ANFIS, see Hong and Lee (1996). In this study, we used the Matlab fuzzy logic toolbox to implement ANFIS. In particular, we used the fuzzy *c*-means clustering method to reduce and simplify the data dimensionality. Moreover, a hybrid of back-propagation and the least squares algorithm was utilized to tune the parameters of the membership functions (Chen, 2013). We used a Gaussian function as the fuzzy membership function (MF).

3.3.5. Genetic algorithm (GA)

GAs have been used in many studies as tools for search and optimization, and GA is still the most popular method for these purposes (Aguilar-Rivera, Valenzuela-Rendón, & Rodríguez-Ortiz, 2015). GA is mainly used to solve optimization problems, where an important goal is generally to rapidly obtain a satisfactory solution, although it may be suboptimal. Therefore, as in Ong, Huang, and Tzeng (2005) and García and Kristjanpoller (2019), GA was employed to obtain the same number of trials based on the same number of different parameter values in this study. In particular, we used GA to determine the time lags for the input factors in the model and the parameters in different models.

4. Experimental results

4.1. Stage I: Modeling for Q1

In this stage, we aimed to identify the predictability of the economic and technology factors, and to screen for more effective predictors. First, we assumed that the economic and technology determinants of the Bitcoin exchange rate would change in different periods. As mentioned in Section 3.2, RF and ANN were employed for feature selection. The sensitivity analysis method is applied to these models to measure the importance of economic and technology factors. Figs. 4–7 show the ranking of the importance scores for each factor in the four periods. From Figs. 4–7 we can see the following.

(a) The Bitcoin exchange rates in the four periods were influenced by different economic and technology factors, thereby supporting our assumptions.

(b) From a technological perspective, when the Bitcoin exchange rate increased and decreased sharply, public attention appeared to play a more important role. These two variables generally caused short-term shocks to the public interest and affected investor sentiment. In terms of blockchain information, we found that although the market capitalization always had a high impact on the Bitcoin exchange rate, the most important factors that affected the currency changed constantly. In contrast, the influence of the block time was significantly lower than that of the other indicators, where it was close to zero. In addition, the average transaction fee was a strong predictor of the Bitcoin exchange rate and its importance always exceeded 0.75. Interestingly, although the market prices were tied to the mining costs, the effects of mining difficulty will diminish over time as the efficiency of mining technology increases.

(c) From an economic perspective, the Bitcoin exchange rate was mainly a reaction to market activities, thereby indicating that macroeconomic development is likely to cause short-term fluctuations in the Bitcoin market. On the other hand, although the importance of foreign exchange was not high, it always had some effect.

(d) The number of important factors was significantly higher in the fluctuation period for the Bitcoin exchange rate (from July 1, 2014 to December 31, 2017) compared with that in the stabilization period (from July 1, 2013 to December 31, 2014), thereby indicating that when the Bitcoin exchange rate was unstable, economic and technology factors were more likely to directly determine changes in the exchange rate.

Furthermore, based on the sensitivity analysis, the crossover method was used to eliminate factors with importance scores less than 0.6 and obtain a set of potential predictors. Table 2 summarizes the economic and technology predictors selected using the feature selection method for the four periods.

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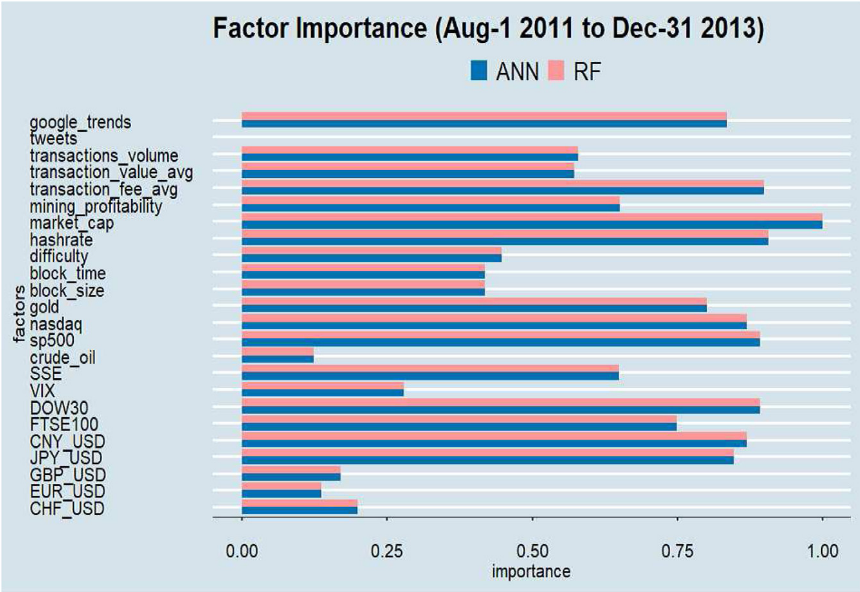

Fig. 4. Importance of various factors from August 1, 2011 to December 31, 2013.

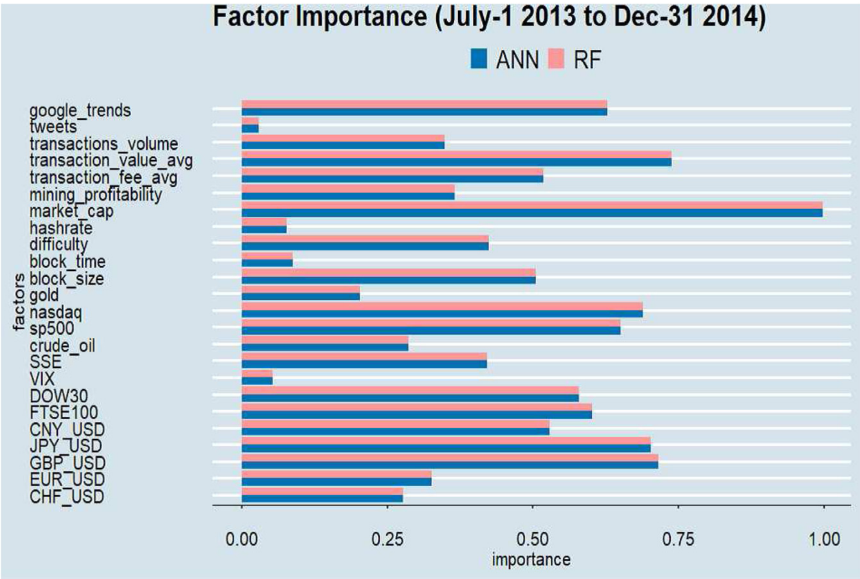

Fig. 5. Importance of various factors from July 1, 2013 to December 31, 2014.

4.2. Stage II: Modeling for Q2

In this section, we assumed that economic and technology determinants could drive changes in the Bitcoin exchange rate. As mentioned in Section 3.3, the economic and technology predictors identified in the first stage were used as inputs for the LSTM, whereas the previous Bitcoin exchange rates were used as inputs for the ARIMA, SVR, ANFIS, and LSTM.

The RMSE, MAPE, MAE, and DA were used as metrics to evaluate the predictive performance of the different models. The first three metrics are the most commonly used for regression problems. Lower values for these indicators indicate better fits for models. In addition, given that the aim of forecasting is to support or improve decision making by business practitioners, we also use the DA to measure the ability to predict the direction of changes. A higher DA value indicates better forecasting performance. The four metrics are defined as follows:

$$RMSE = \frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t - y_t)^2, \tag{13}$$

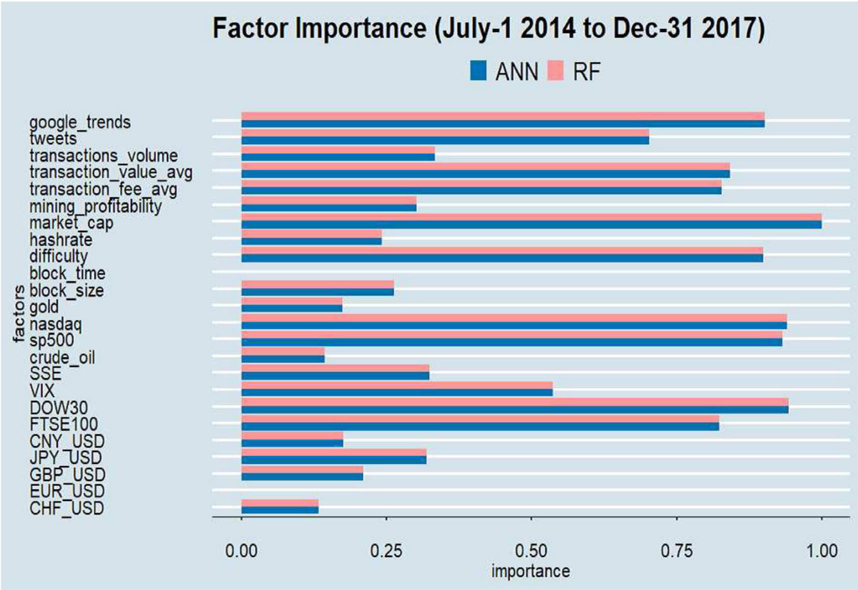

Fig. 6. Importance of various factors from July 1, 2014 to December 31, 2017.

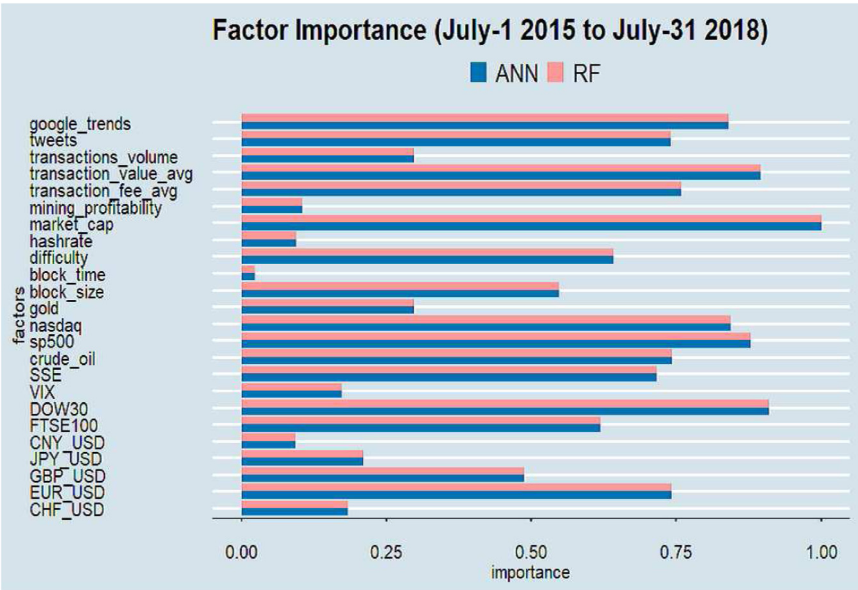

Fig. 7. Importance of various factors from July 1, 2015 to July 31, 2018.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|\hat{y}_t - y_t|}{y_t}, \tag{14}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|\hat{y}_t - y_t|, \tag{15}$$

$$DA = \frac{100}{n}\sum_{t=1}^{n} d_t, \tag{16}$$

where $\hat{y}_t$ corresponds to the volatility forecast for time t, y_t is the actual price at time t, n is the number of forecast periods, and

$$d_t = \begin{cases} 1, & (y_t - y_{t-1})(\hat{y}_t - \widehat{y_{t-1}}) \geq 0, \\ 0, & \text{otherwise.} \end{cases}$$

Moreover, we used the model confidence set (MCS) test introduced by Hansen, Lunde, and Nason (2003) and Hansen, Lunde, and Nason (2011) to conduct statistical tests of performance. The MCS test has been used widely to evaluate the predictive abilities of different models (García & Kristjanpoller, 2019; Qiao, Teng, Li, & Liu, 2019; Tian, Yang, & Chen, 2017). In this study, we used the test

Table 2
Economic and technology predictors for the four periods.

Period	Determinants			
	Economic		Technology	
January 1, 2011 to December 31, 2013	CNY FTSE100 S&P500 Gold price	JPY DOW30 NASDAQ	Market capitalization Average transaction value Average transaction fee	Difficulty Google Trends
July 1, 2013 to December 31, 2014	GBP FTSE100 NASDAQ	JPY DOW30	Market capitalization Average transaction value	Google Trends
July 1, 2014 to Dec 31, 2017	FTSE100 SSE NASDAQ	DOW30 S&P500	Average transaction fee Market capitalization Average transaction value Google Trends	Block size Difficulty Tweets
July 1, 2015 to July 31, 2018	EUR DOW30 Crude oil price NASDAQ	FTSE100 SSE S&P500	Market capitalization Average transaction value Average transaction fee	Google Trends tweets

following statistics:

$$T_{R,M} = \max_{i,j\in M} \frac{|\bar{d}_{ij}|}{\sqrt{\hat{var}(\bar{d}_{ij})}}, \tag{17}$$

$$T_{max,M} = \max_{i\in M} \frac{\bar{d}_{i,.}}{\sqrt{\hat{var}(\bar{d}_{i,.})}}, \tag{18}$$

where d_{ij} denotes the loss differential between models i and j, $d_{i,.}$ is the simple loss of the ith model relative to the averages losses across models in M, and $\hat{var}(\bar{d}_{ij})$ and $\hat{var}(\bar{d}_{i,.})$ are the bootstrapped estimates of $var(\bar{d}_{ij})$ and $var(\bar{d}_{i,.})$, respectively.

The MCS test procedure assigns a p-value to each model in the initial set. For a given model $i \in M$, the MCS p-value $\hat{p}_i^*$ is the threshold confidence level α that determines whether or not a model belongs to the MCS. It holds that $i \in M_{1-\alpha}^*$ only if $\hat{p}_i^* \geq \alpha$.

4.2.1. Predictive performance evaluations

GA was applied in this study in order to obtain the parameter values for different models in the same number of experiments. The parameters for GA were set as follows: population size = 30, function dimension = 1.0, crossover probability = 0.9, mutation probability = 0.1, and maximum generation number = 100. We obtained the values of the control parameters employed for different models by using GA. The results are shown in Table 3.

Table 3
Parameter settings for different models.

Model	Parameter	Value
ARIMA	p^*	[1, 30]
	d^*	[1, 3]
	q^*	[1, 25]
SVR	Input (lags)*	[1, 30]
	g^*	[0.001, 1]
	C^*	[1, 10000]
	ϵ^*	[0.01, 1]
ANFIS	Input (lags)*	[1, 30]
	Fuzzy structure	Sugeno-type
	Clustering method	Fuzzy c-means
	MF type	Gaussian
	Optimization	Hybrid
	Fuzzy rules*	[2, 30]
LSTM	Input (lags)*	[1, 30]
	Activation function	Sigmoid
	Learning rate	0.01
	Nodes in hidden layer*	[1, 30]
	Dropout value	0.1
	Longest training duration	1000
	Loss function	Mean square error

In addition, in order to obtain more information about the overall distribution of the results, each model obtained using GA was run 20 times independently. Tables 4–7 summarize the performance metrics for the different models in terms of the RMSE, MAPE, MAE, and DA based on four statistical indicators comprising the maximum, minimum, mean, and standard deviation (SD). The best results are shown in bold. Figs. 8–11 compare the overall performance of the different models based on box plots.

From Tables 4–7 and Figs. 8–11, we can draw the following conclusions.

First, for the four benchmark models based on previous exchange rates, i.e., ARIMA, ANFIS, SVR, and LSTM, the AI models could fit the original time series in a nonlinear manner and ARIMA did not obtain inferior performance. For example, during the period from July 1, 2013 to December 31, 2014, in terms of the mean and minimum, the MAPE obtained by ARIMA was superior to those obtained by SVR, ANFIS, and LSTM.

Second, the LSTM obtained a higher DA by using the economic and technology predictors. The SD obtained by LSTM using the predictors was relatively large, but it also had larger mean, minimum, and maximum values. In particular, Bitcoin fell sharply during the period from July 1, 2015 to July 31, 2018. Moreover, for the benchmark models based on the previous exchange rates, the maximum, minimum, and mean values of the DA were less than 50, but the corresponding values were greater than 50 with LSTM using the predictors.

Table 4
Performance of different models in terms of RMSE.

Period	Models	Input data	Mean	SD	Minimum	Maximum
January 1, 2011 to December 31, 2013	ARIMA	BTC/USD	74.9701	6.7004	65.3764	83.1288
	SVR	BTC/USD	62.1670	2.1799	59.6526	64.3467
	ANFIS	BTC/USD	60.4807	0.7374	59.5890	61.5999
	LSTM	BTC/USD	59.1246	0.4421	58.7589	59.8569
	LSTM	Predictors	**57.7992**	**0.1902**	**57.5802**	**58.0164**
July 1, 2013 to December 31, 2014	ARIMA	BTC/USD	12.5266	0.4025	12.2653	13.2399
	SVR	BTC/USD	13.0610	0.4323	12.4952	13.5892
	ANFIS	BTC/USD	12.7371	0.1278	12.5831	12.8384
	LSTM	BTC/USD	12.7501	0.2255	12.5691	13.1200
	LSTM	Predictors	**12.0632**	**0.0821**	**11.9929**	**12.1912**
July 1, 2014 to December 31, 2017	ARIMA	BTC/USD	984.2032	76.7176	912.2297	1114.4932
	SVR	BTC/USD	853.6571	25.8649	838.9897	899.5682
	ANFIS	BTC/USD	851.2018	7.1635	844.8778	860.7440
	LSTM	BTC/USD	871.1777	**6.2584**	865.1280	881.6065
	LSTM	Predictors	**798.0600**	11.0990	**786.7549**	**812.2600**
July 1, 2015 to July 31, 2018	ARIMA	BTC/USD	260.9211	34.1338	237.5558	318.1653
	SVR	BTC/USD	251.6057	14.6255	237.3760	275.5415
	ANFIS	BTC/USD	253.1198	12.1703	241.5469	273.1529
	LSTM	BTC/USD	238.9585	5.4640	234.6468	248.3200
	LSTM	Predictors	**236.8888**	**3.5756**	**233.8830**	**240.9976**

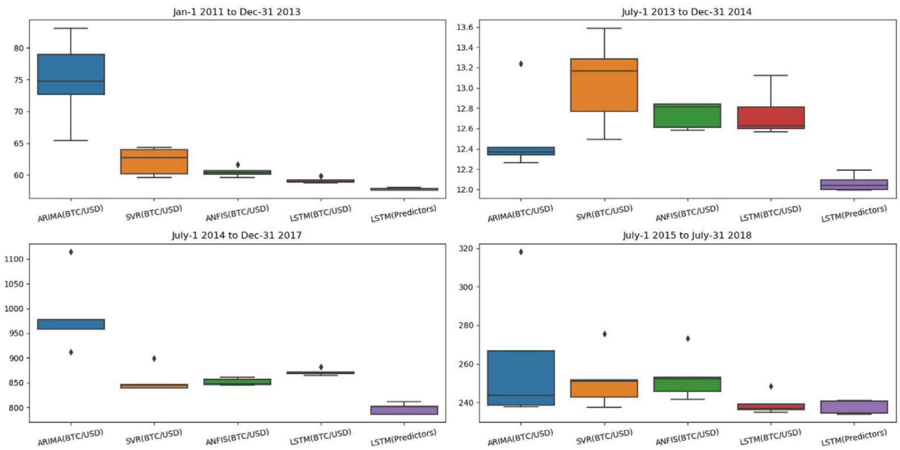

Fig. 8. Overall performance of different models in terms of RMSE.

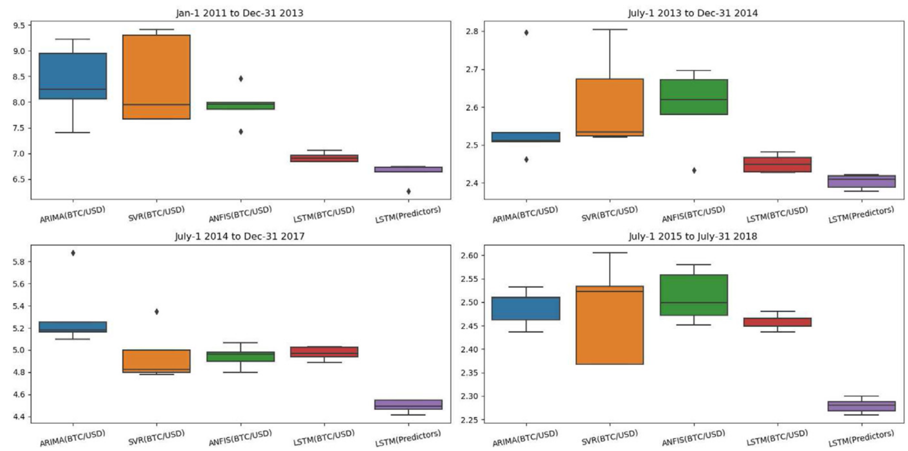

Fig. 9. Overall performance of different models in terms of MAPE.

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Table 5
Performance of different models in terms of MAPE.

Period	Models	Input data	Mean	SD	Minimum	Maximum
January 1, 2011 to December 31, 2013	ARIMA	BTC/USD	8.3780	0.7227	7.4105	9.2187
	SVR	BTC/USD	8.4035	0.8824	7.6709	9.4171
	ANFIS	BTC/USD	7.9384	0.3680	7.4246	8.4555
	LSTM	BTC/USD	6.9238	0.0929	6.8429	7.0625
	LSTM	Predictors	**6.6743**	**0.0558**	**6.6262**	**6.7441**
July 1, 2013 to December 31, 2014	ARIMA	BTC/USD	2.5623	0.1334	2.4619	2.7964
	SVR	BTC/USD	2.6114	0.1260	2.5208	2.8051
	ANFIS	BTC/USD	2.6002	0.1037	2.4335	2.6963
	LSTM	BTC/USD	2.4506	0.0232	2.4280	2.4810
	LSTM	Predictors	**2.4031**	**0.0195**	**2.3775**	**2.4210**
July 1, 2014 to December 31, 2017	ARIMA	BTC/USD	5.3138	0.3204	5.0964	5.8787
	SVR	BTC/USD	4.9501	0.2396	4.7793	5.3495
	ANFIS	BTC/USD	4.9411	0.1009	4.7967	5.0691
	LSTM	BTC/USD	4.9699	0.0608	4.8868	5.0290
	LSTM	Predictors	**4.4920**	**0.0568**	**4.4147**	**4.5479**
July 1, 2015 to July 31, 2018	ARIMA	BTC/USD	2.4903	0.0396	2.4367	2.5330
	SVR	BTC/USD	2.4793	0.1070	2.3672	2.6051
	ANFIS	BTC/USD	2.5121	0.0550	2.4517	2.5800
	LSTM	BTC/USD	2.4564	0.0171	2.4372	2.4810
	LSTM	Predictors	**2.2793**	**0.0155**	**2.2602**	**2.3000**

Table 6
Performance of different models in terms of MAE.

Period	Models	Input data	Mean	SD	Minimum	Maximum
January 1, 2011 to December 31, 2013	ARIMA	BTC/USD	55.0827	5.6430	47.8364	61.9647
	SVR	BTC/USD	51.4289	3.3296	48.2221	55.2035
	ANFIS	BTC/USD	49.4400	1.5025	47.4757	51.6116
	LSTM	BTC/USD	44.6732	0.4629	44.2826	45.3982
	LSTM	Predictors	**43.5189**	**0.3364**	**43.2372**	**43.9799**
July 1, 2013 to December 31, 2014	ARIMA	BTC/USD	9.3182	0.5112	8.9320	10.2144
	SVR	BTC/USD	9.4710	0.4249	9.1214	10.1369
	ANFIS	BTC/USD	9.2389	0.3280	8.8648	9.7364
	LSTM	BTC/USD	9.1718	0.4727	8.8512	10.0000
	LSTM	Predictors	**8.7512**	**0.0787**	**8.6623**	**8.8502**
July 1, 2014 to December 31, 2017	ARIMA	BTC/USD	658.8201	50.9604	621.6099	748.2823
	SVR	BTC/USD	585.0512	11.5520	577.2493	605.4630
	ANFIS	BTC/USD	595.9921	10.7721	580.1585	607.9229
	LSTM	BTC/USD	606.6807	8.5154	596.0503	618.6798
	LSTM	Predictors	**548.1484**	**8.4943**	**533.5911**	**555.3670**
July 1, 2015 to July 31, 2018	ARIMA	BTC/USD	195.9379	31.6881	167.4211	245.0000
	SVR	BTC/USD	182.8373	17.9003	168.6144	213.8985
	ANFIS	BTC/USD	179.8682	15.6268	163.3927	205.3723
	LSTM	BTC/USD	170.2805	**3.4699**	168.2333	176.4209
	LSTM	Predictors	**161.6107**	5.1881	**156.2296**	**169.5340**

Third, for each period, the RMSE, MAPE, and MAE values obtained by the LSTM using the economic and technology predictors indicated better performance in terms of the four statistical indicators comprising the the minimum, maximum, mean, and SD. In other words, the LSTM using predictors has superior predictive performance in terms of the accuracy, stability, and robustness compared with the models using previous exchange rates.

4.2.2. Confidence test

The MCS test was conducted to analyze the significance of the results. As recommended by Hansen et al. (2011), the block length and number of bootstrap samples were set to 2 and 10,000, respectively. Tables 8–10 present the optimal superior set of models (SSM) and the corresponding p-values at the 20% significance levels. In these tables, $Rank_M$ and $Rank_R$ are the models sorted according to two statistics comprising $T_{R,M}$ and $T_{max,M}$, respectively, and p_M and p_R are the corresponding p-values for the whole set of rankings. Tables 8–10 clearly demonstrate that including the economic and technology determinants could yield better predictive performance. For example, according to the three evaluation indicators, the benchmark models based on the previous exchange rates could not pass the MCS tests in some cases, whereas the LSTM using the predictors passed all of the tests. It should be noted that the values of $T_{R,M}$ and $T_{max,M}$ obtained by the LSTM using the predictors were 1, thereby confirming the superior advantage of the model constructed for Bitcoin exchange rate forecasting.

In general, the experimental results presented in Sections 4.2.1 and 4.2.2 support our overall assumption that: "The Bitcoin exchange rate is driven by different economic and technology determinants in different periods". Thus,

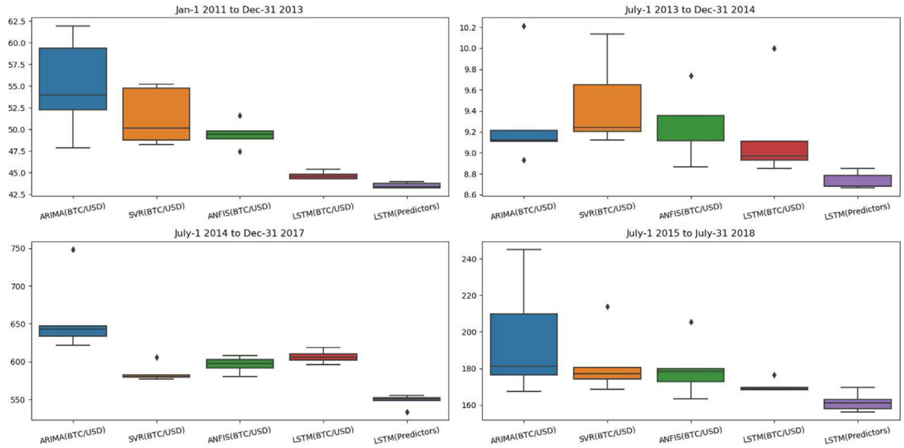

Fig. 10. Overall performance of different models in terms of MAE.

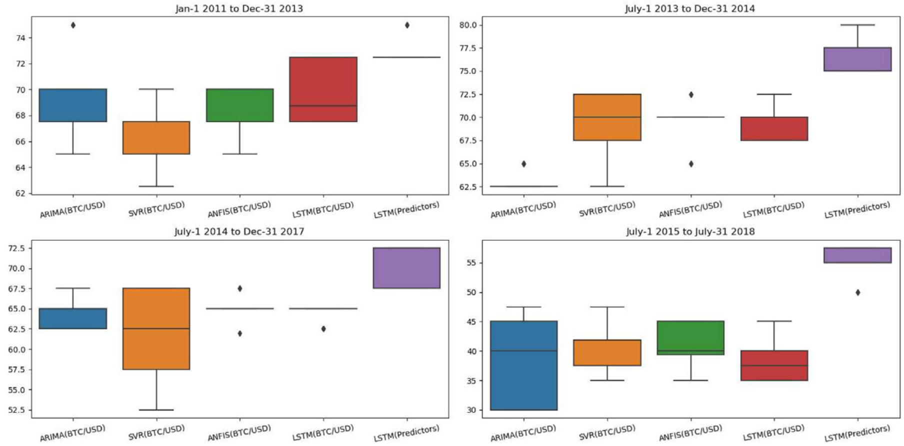

Fig. 11. Overall performance of different models in terms of DA.

Table 7
Performances of different models in terms of DA.

Period	Models	Input data	Mean	SD	Minimum	Maximum
January 1, 2011 to December 31, 2013	ARIMA	BTC/USD	69.0000	3.4793	65.0000	75.0000
	SVR	BTC/USD	66.0000	2.6157	62.5000	70.0000
	ANFIS	BTC/USD	69.0000	1.7014	65.0000	70.0000
	LSTM	BTC/USD	68.5000	**1.2566**	67.5000	70.0000
	LSTM	Predictors	**71.7500**	2.4468	**70.0000**	**75.0000**
July 1, 2013 to December 31, 2014	ARIMA	BTC/USD	63.0000	**1.0260**	62.5000	65.0000
	SVR	BTC/USD	69.0000	3.8389	62.5000	72.5000
	ANFIS	BTC/USD	69.5000	2.5131	65.0000	72.5000
	LSTM	BTC/USD	69.0000	2.0520	67.5000	72.5000
	LSTM	Predictors	**76.5000**	2.0520	**75.0000**	**80.0000**
July 1, 2014 to December 31, 2017	ARIMA	BTC/USD	64.5000	1.9194	62.5000	67.5000
	SVR	BTC/USD	61.5000	5.9824	52.5000	67.5000
	ANFIS	BTC/USD	65.2250	1.1863	62.0000	67.5000
	LSTM	BTC/USD	64.5000	**1.0260**	62.5000	65.0000
	LSTM	Predictors	**68.5000**	2.0520	**67.5000**	**72.5000**
July 1, 2015 to July 31, 2018	ARIMA	BTC/USD	38.5000	7.5394	30.0000	47.5000
	SVR	BTC/USD	40.2500	4.5088	35.0000	47.5000
	ANFIS	BTC/USD	40.7500	3.1519	35.0000	45.0000
	LSTM	BTC/USD	38.5000	3.6635	35.0000	45.0000
	LSTM	Predictors	**55.0000**	**2.8098**	**50.0000**	**57.5000**

Table 8
MSC test results based on the RMSE loss function.

Period	Models	Input data	$T_{max,M}$	$Rank_M$	p_M	$T_{R,M}$	$Rank_R$	p_R
January 1, 2011 to December 31, 2013	ARIMA	BTC/USD	0.8304	3	0.5993	0.3852	3	0.2410
	SVR	BTC/USD	0.5993	5		0.2494	4	
	ANFIS	BTC/USD	0.6939	4		0.2410	5	
	LSTM	BTC/USD	1.0000	2		0.4665	2	
	LSTM	Predictors	1.0000	1		1.0000	1	
July 1, 2013 to December 31, 2014	ARIMA	BTC/USD	0.9983	4	0.9771	0.9777	5	0.9777
	SVR	BTC/USD	0.9771	5		0.9904	2	
	ANFIS	BTC/USD	1.0000	3		0.9817	4	
	LSTM	BTC/USD	1.0000	2		0.9864	3	
	LSTM	Predictors	1.0000	1		1.0000	1	
July 1, 2014 to December 31, 2017	ARIMA	BTC/USD	–	–	0.3535	–	–	0.2056
	SVR	BTC/USD	0.5502	2		0.3099	2	
	ANFIS	BTC/USD	0.3535	3		0.2056	3	
	LSTM	BTC/USD	–	–		–	–	
	LSTM	Predictors	1.0000	1		1.0000	1	
July 1, 2015 to July 31, 2018	ARIMA	BTC/USD	–	–	0.4693	–	–	0.2054
	SVR	BTC/USD	0.4693	3		–	–	
	ANFIS	BTC/USD	0.9615	2		0.2054	2	
	LSTM	BTC/USD	–	–		–	–	
	LSTM	Predictors	1.0000	1		1.0000	1	

Table 9
MCS test results based on the MAPE loss function.

Period	Models	Input data	$T_{max,M}$	$Rank_M$	p_M	$T_{R,M}$	$Rank_R$	p_R
January 1, 2011 to December 31, 2013	ARIMA	BTC/USD	0.5007	3	0.4976	0.3596	3	0.2187
	SVR	BTC/USD	–	–		–	–	
	ANFIS	BTC/USD	0.4976	4		0.2187	4	
	LSTM	BTC/USD	1.0000	2		0.5726	2	
	LSTM	Predictors	1.0000	1		1.0000	1	
July 1, 2013 to December 31, 2014	ARIMA	BTC/USD	0.9989	4	0.9365	0.9544	2	0.7395
	SVR	BTC/USD	0.9365	5		0.9530	3	
	ANFIS	BTC/USD	1.0000	3		0.8909	4	
	LSTM	BTC/USD	1.0000	2		0.7395	5	
	LSTM	Predictors	1.0000	1		1.0000	1	
July 1, 2014 to December 31, 2017	ARIMA	BTC/USD	–	–	0.3341	–	–	0.2047
	SVR	BTC/USD	0.5322	2		0.3077	2	
	ANFIS	BTC/USD	0.3341	3		0.2047	3	
	LSTM	BTC/USD	–	–		–	–	
	LSTM	Predictors	1.0000	1		1.0000	1	
July 1, 2015 to July 31, 2018	ARIMA	BTC/USD	0.9817	3	0.6387	0.5933	2	0.4063
	SVR	BTC/USD	0.8903	4		0.4063	3	
	ANFIS	BTC/USD	1.0000	2		–	–	
	LSTM	BTC/USD	0.6387	5		–	–	
	LSTM	Predictors	1.0000	1		1.0000	1	

better predictive performance can be obtained by using the information hidden in economic and technology determinants rather than by using the previous exchange rates.

5. Conclusion

Bitcoin is a successful cryptocurrency and it has been studied extensively in the fields of economics and computer science. In this study, we examined whether economic and technology determinants can accurately predict the Bitcoin exchange rate. We collected and preprocessed data from August 1, 2011 to July 31, 2018, which covered the 24 factors considered in previous studies. In addition, in order to reveal the dynamic changes in the Bitcoin market, we divided the data set into four periods. A two-stage prediction model was then developed. In the first stage, we used two feature selection methods comprising ANN and RF to measure the importance of the economic and technology factors, and obtained a subset of potential predictors. After comparing the importance rankings for various factors in the four data sets, we found that the Bitcoin exchange rate was affected by different economic and technology factors in different periods. In the second stage, the predictors were as inputs for prediction by the LSTM, but without considering the previous Bitcoin exchange rate. In addition, the ANFIS, ARIMA, SVR and LSTM models made predictions based on the previous Bitcoin exchange rates. The results clearly demonstrated that using the economic and technology determinants was effective for predicting the Bitcoin exchange rate.

In future research, we will consider more factors in our proposed two-stage prediction model, such as investor sentiment and government regulation. Moreover, we will

Table 10
MCS test results based on the MAE loss function.

Period	Models	Input data	$T_{max,M}$	$Rank_M$	p_M	$T_{R,M}$	$Rank_R$	p_R
January 1, 2011 to December 31, 2013	ARIMA	BTC/USD	0.8201	3	0.5996	0.3650	3	0.2349
	SVR	BTC/USD	0.6080	5		0.2502	4	
	ANFIS	BTC/USD	0.6795	4		0.2349	5	
	LSTM	BTC/USD	1.0000	2		0.4633	2	
	LSTM	Predictors	1.0000	1		1.0000	1	
July 1, 2013 to December 31, 2014	ARIMA	BTC/USD	0.9976	4	0.9684	0.9511	3	0.7271
	SVR	BTC/USD	0.9684	5		0.9821	2	
	ANFIS	BTC/USD	1.0000	3		0.8883	4	
	LSTM	BTC/USD	1.0000	2		0.7271	5	
	LSTM	Predictors	1.0000	1		1.0000	1	
July 1, 2014 to December 31, 2017	ARIMA	BTC/USD	–	–	0.3519	–	–	0.2090
	SVR	BTC/USD	0.5485	2		0.3039	2	
	ANFIS	BTC/USD	0.3519	3		0.2090	3	
	LSTM	BTC/USD	–	–		–	–	
	LSTM	Predictors	1.0000	1		1.0000	1	
July 1, 2015 to July 31, 2018	ARIMA	BTC/USD	0.9821	3	0.6347	0.5857	2	0.4085
	SVR	BTC/USD	0.8919	4		0.4085	3	
	ANFIS	BTC/USD	1.0000	2		–	–	
	LSTM	BTC/USD	0.6347	5		–	–	
	LSTM	Predictors	1.0000	1		1.0000	1	

apply the proposed model to other prediction problems, such as stock trends and traffic flows.

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