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Complexity analysis and forecasting of variations in cryptocurrency trading volume with support vector regression tuned by Bayesian optimization under different kernels: An empirical comparison from a large dataset

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ABSTRACT

When cryptocurrency markets generate billions of dollars, it becomes interesting to forecast variation in volume of transactions for better trading and for better management of blockchain platforms. This study investigates how kernel choice influences the forecasting performance of the support vector regression (SVR) in predicting cryptocurrency trading volume. Three common kernels are considered; namely, linear, polynomial, and radial basis function (RBF). In addition, we make use of Bayesian optimization (BO) method to tune key parameters of the SVR, hereafter referred as SVR-BO. Besides, we examine the nonlinear dynamics of variation in volume of transactions by computing Hurst exponent, sample entropy, and largest Lyapunov exponent and found evidence of anti-persistence, significant randomness, and presence of chaos. Well-known ARIMA process, Lasso regression and Gaussian regression are used as benchmark models in the forecasting task. The root mean of squared errors (RMSE) and mean average error (MAE) are adopted as main performance metrics. Forecasting simulations are applied to thirty cryptocurrencies. The results from 180 experiments show that the SVR-BO with RBF kernel outperforms all models when used to predict next-day trading volume while SVR-BO with polynomial kernel outperforms all remaining models when used to predict next-week trading volume. Besides, Gaussian regression performs better than ARIMA process and Lasso regression on both daily and weekly data.

1. Introduction

Unlike cash, cryptocurrency is obviously a digital money used primarily online. Indeed, cryptocurrency is a virtual currency secured by cryptography that makes it difficult to counterfeit. Since its introduction in 2009, the cryptocurrency market is attracting a large number of transactions. In order to better understand the mechanics of cryptocurrency markets, recent studies have examined various issues regarding cryptocurrency prices; including mapping cryptocurrencies to the complexity-entropy causality plane (Stosic et al., 2019a), agglomerative hierarchical clustering (Song et al., 2019), volatility modeling (Lahmiri, Bekiros, & Salvi, 2018; Omane-Adjepong et al., 2019), multifractal analysis (Cheng et al., 2019; Lahmiri & Bekiros, 2019a; Stavroyiannis et al., 2019; Zhang et al., 2019), tail-risk vulnerability (Borri, 2019), and volatility (Kristjanpoller & Minutolo, 2018; Lahmiri & Bekiros, 2021a; Peng et al., 2018; Yu, 2019) and price forecasting (Alonso-Monsalve et al., 2020; Catania et al., 2019; Lahmiri & Bekiros, 2019b, 2020, 2021b).

Although attention has been given to the analysis and modeling of cryptocurrency price and volatility, only a limited number of studies has focused on studying the volume of transactions. For instance, it was found that cryptocurrency trading volume carries useful information to predict extreme negative and positive returns of all cryptocurrencies; however, it can predict volatility for only a limited number of cryptocurrencies when the volatility is low (Bouri et al., 2019). Besides, it was found that volume changes follow different multifractal dynamics (Stosic et al., 2019b), there exists power-law correlation between price and volume (Zhang et al., 2018), and that the frequency of Google

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searches leads to a surge in Bitcoin trading volume (Nasir et al., 2019).

The motivations behind forecasting volume of cryptocurrencies follow. First, as forecasting is an important task in financial time series analysis and modeling, the knowledge of the future variation in volume of transactions provides valuable guidance in developing profitable trading strategies. Specifically, trading volume can be a substitute for information in the study of cryptocurrency price dynamics and good management of blockchain platforms. Second, can be employed as a predictor of returns and volatility since it carries valuable information regarding expectations of investors.

In this regard, the primary goal of this paper is to investigate the predictability of cryptocurrency trading volume. To this end, the support vector regression (SVR) (Vapnik et al., 1996) is employed under different kernel functions used to nonlinearly map the input–output data. In fact, the main advantage of the SVR is applying the structural risk minimization principle to minimize an upper bound on the generalization error rather than implementing the empirical risk minimization principle to minimize the training error (Vapnik et al., 1996). Therefore, it theoretically guarantees to achieve the global optimum. In addition, the SVR can provide good generalization results even the data sample is small (Vapnik et al., 1996). Bring in mind that the SVR was successfully employed to solve various non-linear regression problems such as forecasting stock price (Lahmiri, 2018), discharge coefficient of a modified labyrinth side weir (Zaji et al., 2016), travel retail industry sales (Karmy & Maldonado, 2019), electric load (Maldonado et al., 2019; Yang et al., 2019), wind tunnel performance (Yan et al., 2020), and wind speed (Liu et al., 2019).

Besides, Bayesian optimization (BO) (Gelbart et al., 2014) is employed to tune key parameters of the SVR since this technique is fast and effective (Kazakeviciute et al., 2016; Lahmiri & Shmuel, 2019). For robustness of the results, the SVR is applied to predict trading volume of a large data set composed of thirty cryptocurrencies. Then, formal statistical tests are applied to the estimated out-of-sample forecasting errors to check for presence of differences between populations of forecasts across different kernels. Besides, three different metrics belonging to statistical physics measures are employed to assess fractality, randomness, and chaos in cryptocurrency volume data. They are respectively detrended fluctuation analysis (DFA) (Peng et al., 1994), sample entropy (SampEn) (Richman & Moorman, 2000), and the largest Lyapunov exponent (LLE) based on the method of Rosenstein (Rosenstein et al., 1993). Indeed, they are well suited to describe nonlinear dynamics in nonstationary data with no prior assumptions.

To sum up, the contributions of the current study follow. First, we tackle the problem of forecasting variation in volume of transactions in cryptocurrency. As far as we know, this is the first paper to conduct such investigation. Therefore, this the primary goal of the current empirical study. Second, we use a robust statistical machine learning model; namely, the SVR and investigate the effect of three different kernel choices on the forecasting accuracy; namely, linear, polynomial, and RBF kernel. Indeed, the SVR achieves the global optimum in minimizing the fitting error and provides good generalization results even the data sample is small. Third, Bayesian optimization technique is adopted to find the optimal values of key parameters of the SVR. This optimization technique is fast and statistically robust. Fourth, for robust results and generalization capability, the SVR-BO model is tested on a set composed of thirty different cryptocurrencies. Fifth, complexity in cryptocurrency volume variations is assessed to shed light on the nonlinear dynamics of such time series. Indeed, this is the secondary goal of our empirical study. For instance, it is a complement investigation to understand the nonlinear dynamics in volume variations. At the end, this is the first comprehensive study to predict cryptocurrency volume of transactions and examine the effect of kernel choice on SVR accuracy. Sixth, SVR models are compared against popular statistical models; namely, ARIMA process (Box, 2015), Lasso regression (Tibshirani, 1996), and Gaussian regression (Rasmussen & Williams, 2006).

The reminder of this work is as follows. In Section 2 the support vector regression, Bayesian optimization, and performance metric are described. Section 3 presents the simulation results. Finally, Section 4 briefly discusses the results and concludes the work.

2. Forecasting and optimization methods

Since the primary goal of the current comparative empirical study is to forecast variations in volume of transactions of cryptocurrencies, in this section, we only present SVR, Bayesian optimization and the performance metric; namely, the root mean of squared errors. As the secondary goal is about assessing complexity in such data, details on detrended fluctuation analysis (DFA) (Peng et al., 1994), sample entropy (SampEn) (Richman & Moorman, 2000), and the largest Lyapunov exponent (LLE) based on the method of Rosenstein (Rosenstein et al., 1993) are left to the reader in the respective references. Briefly speaking, they allow measuring fractality, randomness, and chaos in data. Thus, they are appropriate to describe nonlinear dynamics in nonstationary data with no prior assumptions. Thus, they are used as descriptors of nonlinear movements in volume variations.

2.1. The support vector regression

Let $\{(\mathbf{x}_k, \mathbf{y}_k)\}_{k=1}^{N}$ denotes the kth input vector × of the kth training pattern and $\mathbf{y}_k$ represents its corresponding desired output. Then, the regression function f is performed by a linear SVR (Vapnik et al., 1996) and is expressed as follows:

$$f(\boldsymbol{x}) = \boldsymbol{\omega}\boldsymbol{x}^T + b \tag{1}$$

where ×,$\boldsymbol{\omega}$=($\boldsymbol{\omega}_1$, $\boldsymbol{\omega}_2$,…, $\boldsymbol{\omega}_n$) ∈ R^n, $b \in \mathrm{R}$ and T are respectively the input vector, the weight vector, the intercept, and transpose operator. The optimization problem for training the linear SVR is given by:

$$\textit{Minimize } \frac{1}{2}\|\omega\|^2 + C\sum_{k=1}^{N}(\xi_k + \xi_k^*) \tag{2}$$

Subject to,

$$y_k - \boldsymbol{\omega}\boldsymbol{x}_k^T - b \leqslant \varepsilon + \xi_k \textit{ and } \boldsymbol{\omega}\boldsymbol{x}_k^T + b - y_k \leqslant \varepsilon + \xi_k^* \tag{3}$$

where C is the penalty for incorrectly estimating the output associated with input vectors, $\varepsilon > 0$ is the regularization factor that weights the trade-off between the $\mathbf{y}$ estimated value and the target value, and ξ and ξ^* are slack variables, and $k = 1,\ldots,N$. Briefly speaking, the nonlinear support vector regression (SVR) (Vapnik et al., 1996) seeks to solve the following nonlinear regression problems:

$$f(\boldsymbol{x}) = \omega\phi(\boldsymbol{x})^T + b = \sum_{k=1}^{N}(\alpha_k - \alpha_k^*)\,\phi(\boldsymbol{x}_k)\,\phi(\boldsymbol{x}_k)^T + b \tag{4}$$

where $\varphi(\mathbf{x})$ denotes a mapping function that maps the input vector × into a higher dimensional feature space, and where α and α^* are the Lagrange multipliers. The inner product of functions $\varphi(\mathbf{x})$ and $\varphi(\mathbf{x})^T$ can be replaced by a kernel function $K(\bullet)$. Thus, the general form of the SVR is given by:

$$f(\boldsymbol{x}) = \sum_{k=1}^{N}(\alpha_k - \alpha_k^*)\,K(\boldsymbol{x}, \boldsymbol{x}_k) + b \tag{5}$$

In this study, three kernel functions are considered; namely, linear, polynomial, and radial basis function (RBF), respectively expressed as follows:

$$K(x, x_i) = xx_i \tag{6}$$

$$K(x, x_i) = (xx_i + 1)^d \tag{7}$$

$$K(x, x_i) = \exp\left(-\|x - x_i\|^2/\sigma^2\right) \tag{8}$$

Here, d is the order of the polynomial kernel and σ is the width of the RBF. Recall that these kernels have been chosen as they are popular in SVR function approximation.

2.2. Baysian optimization

In Bayesian optimization (BO) framework (Gelbart et al., 2014), an acquisition function is employed to consider both regions where the model believes the objective function is low and regions where uncertainty is high. In practice, there are many different types of acquisition functions. Because of its strong theoretical guarantees and empirical effectiveness (Gelbart et al., 2014), the expected improvement (*EI*) criterion is considered as main acquisition function in our study. Then, if $f(x)$ is the objective function, then, the expected improvement $EI(x,Q)$ is used to evaluate the feasibility of a point × based on the posterior distribution function Q. In this work, objective function is the error function of the SVR and the acquisition function is defined as the expected-improvement function ($EI(x,Q)$). The acquisition function is used to evaluate the "goodness" of the SVR parameters. The expected-improvement function ($EI(x,Q)$) is expressed as follows:

$$EI(x,Q) = E_Q\left[\max\left(0, \mu_Q(x_{best}) - f(x)\right)\right] \tag{9}$$

where x_{best} is the location of the lowest posterior mean and $\mu_Q(xbest)$ is the lowest value of the posterior mean.

The BO is employed to tune the structural parameters of the SVR; namely, the penalty factor C, the regularization factor ε, and the slack variable ξ. Also, BO algorithm is used to find the optimal value of parameter d (the order of the polynomial kernel) and the parameterσ, the width of the radial basis function following a Bayesian rule. Specifically, a probabilistic model is built for each hyperparameter to generate a mapping function from that hyperparameter values to the objective function evaluated on a validation set. The BO technique is employed through k-fold cross validation which is a very popular approach in machine learning algorithms. In this regard, the number of folds is set to ten. More details on BO method can be found in Gelbart et al. (2014).

2.3. Performance measure

As already mentioned, the root mean of squared errors (RMSE) and mean of absolute errors (MAE) are employed as main performance measures. Indeed, they are a standard and popular performance metrics widely used for signal analysis and prediction.

The lower is the RMSE performance metric, the better is the forecasting accuracy. The RMSE is given by:

$$RMSE = \sqrt{n^{-1}\sum_{i=1}^{n}(A_i - P_i)^2} \tag{10}$$

where A and P $\overline{\mathrm{P}}$ represent respectively the actual and predicted value, i is time index, and n is total number of out-of-sample data points. Also, the MAE is expressed as follows:

$$MAE = n^{-1}\sum_{i=1}^{n}(A_i - P_i) \tag{11}$$

Similarly, the lower is the MAE, the better is the forecasting accuracy.

3. Data and results

We gathered data on volume of transactions of thirty cryptocurrencies from yahoo.com for the period from spanning from 16 November 2018 to 16 November 2019. The choice of this period is motivated by forming a large number of cryptocurrencies with significant number of transactions and price movements. In this regard, using SVR is an appropriate choice as it is capable to provide good generalization even from small data and to achieve global optima (Vapnik et al., 1996). The list of cryptocurrencies includes Aragon, Basic Attention Token, Bitcoin Cash, Blocknet, Binance Coin, Bitcoin, Civic, DigixDAO, district0x, Dogecoin, EOS, Ethereum, Ethereum, Gnosis, ICON, Lisk, Litecoin, MaidSafeCoin, MCO, MonaCoin, Nano, NavCoin, Neblio, OmiseGO, Status, Stratis, Substratum, Tether, NEM, and XRP. The change in volume ΔV(t) at time t is calculated as V(t)-V(t-)/V(t). For illustration purpose, Fig. 1 displays Aragon change in volume time series, ΔV(t).

In order to describe variations in the change of volume time series (ΔV(t)), we computed three different nonlinear statistics; namely, the Hurst exponent (HE) by using detrended fluctuation analysis (DFA) (Peng et al., 1994), sample entropy (SampEn) (Richman & Moorman, 2000), and the largest Lyapunov exponent (LLE) based on the method of Rosenstein (Rosenstein et al., 1993). Indeed, the Hurst exponent is useful to evaluate long memory pattern that is hidden in temporal structure of the time series, sample entropy quantifies the rate of information production in the signal, and the largest Lyapunov exponent assesses the existence of chaotic oscillations in the underlying data. Fig. 2 exhibits the boxplots of Hurst exponent (HE), sample entropy (SampEn), and the largest Lyapunov exponent (LLE). In general, based on the respective distributions of HE, SampEn, and LLE, it is obvious that changes in daily volume of cryptocurrencies exhibit anti-persistent dynamics, significant level of randomness, and chaos. In other words, volume variation series exhibit nonlinear behavior and also some level of predictability. Hence, our choice to use support vector regression to model and predict future movement in volume of cryptocurrencies is appropriate since support vector regression are nonlinear predictive systems capable to map the data into a high dimensional space. In this regard, we used the standard protocol in machine learning literature for time series forecasting consisting on setting 80 % of the data for training the predictive model (for instance, the SVR-BO) and the remaining 20 % for testing.

It is very important to define and select meaningful inputs for the forecast of variation in trading volume. In this regard, the previous variations in trading volume are used as inputs. Especially, the last 5-days variations are fed to the predictive SVR-BO to generate forecasts. Indeed, there is no theoretical approach on how to determine the number of lags; hence, we used the last 5-days trading data as inputs as it is an effective and simple approach in building parsimonious financial time series forecasting models (Lahmiri & Bekiros, 2020; 2021b). For illustration purpose, Fig. 3 shows the graphical output from Bayesian optimization used to optimize the SVR parameters; specifically, it plots the minimum objective function against the number of function evaluations for each type of kernel. The Bayesian optimization algorithm required thirty iterations. The minimum observed value of the objective function and the estimated minimum simultaneously converged at the ninth, fifth, and tenth iteration respectively for the linear, polynomial, and radial basis function kernel. In this regard, it is worth mentioning that the processing time used by Bayesian optimization method to tune SVR when trained with linear kernel is 377.2608 s, with polynomial kernel is 110.2748 s, and with RBF kernel is 27.4173. Therefore, Bayesian optimization method is fast; especially when used to tune parameters of the RBF kernel.

Table 1 reports the obtained performance metrics along their respective average and stadard deviation when models are used to predict next-day and next-week trading volume seperatly. we focus on these two different horizons because of the limited data size. As shown in Table 1, for daily data, the SVR-BO with RBF kernel outperformed all other models in terms of RMSE and MAE. In addition, reference models (ARIMA, Lasso, Gaussian regression) underpperformed all SVR-BO models. Besides, for weekely data, the SVR-BO with polynomial kernel outperformed all remaining models in terms of RMSE and MAE. Additionnaly, benchmark models obtained higher forecasting errors compared to all SVR-BO models. Finally, it is worth to mention that Gaussian regression performed better than ARIMA process and Lasso regression on both daily and weekely data.

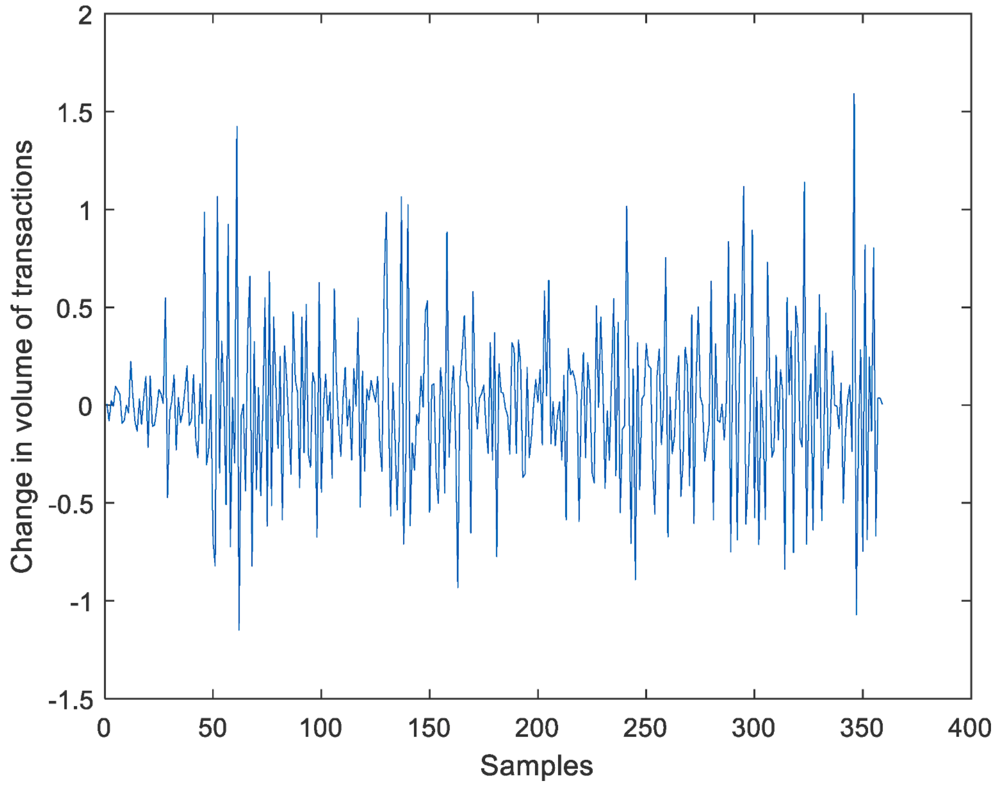

Fig. 1. Plot of Aragon change in volume time series (ΔV(t)).

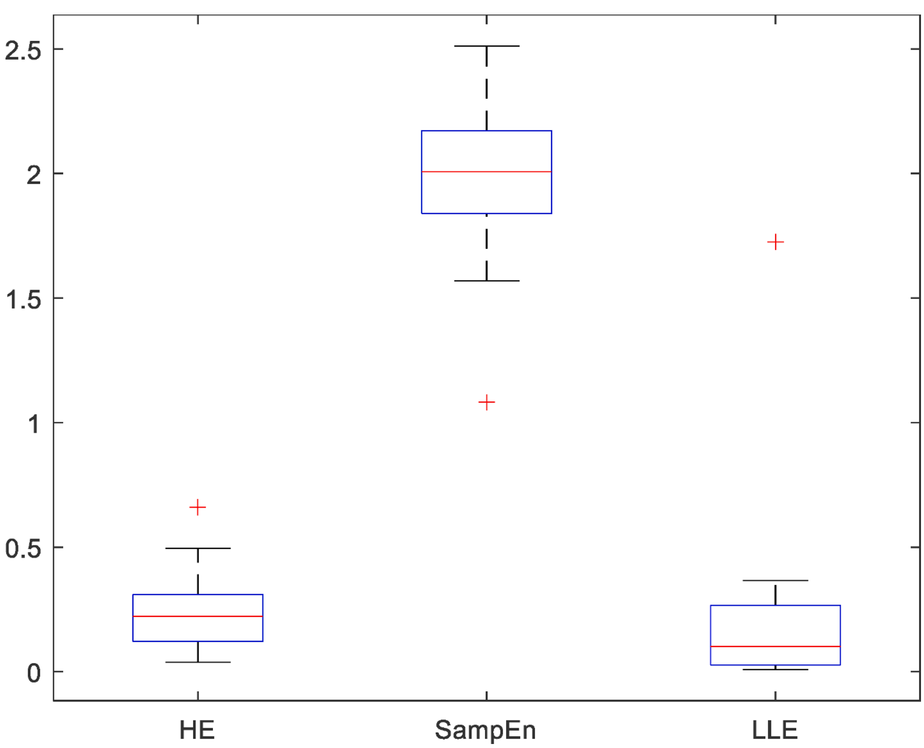

Fig. 2. Boxplots of values of Hurst exponent (HE), sample entropy (SampEn), and largest Lyapunov exponent (LLE). They are computed from changes of volume of transactions of thirty cryptocurrencies. The horizontal line indicate the mean of the distribution. As seen, the HE sample mean is clearly below 0.5 which indicates that volume variation series are antipersistent. The SampEne mean is close to 2; hence, volume variation series exhibit some level of randomness. The sample mean of LLE is positive meaning that volume series are chaotic.

4. Discussion and conclusion

The cryptocurrency markets have been growing exponentially since inception. This remarkable development attracted the attention of governmental regulation authorities, large financial institutions and all investors at large. Consequently, the relative academic literature on the topic is growing fast; including study of connectivity among markets, volatility modeling, multi-scale analysis of prices and returns, and price and return forecasting. However, there are still uncharted territories. Specifically, nonlinear analysis and modeling and forecasting of volume of transactions data are hot topics that are not explored. Therefore, the primary goal of our paper is to complement and enrich the literature by

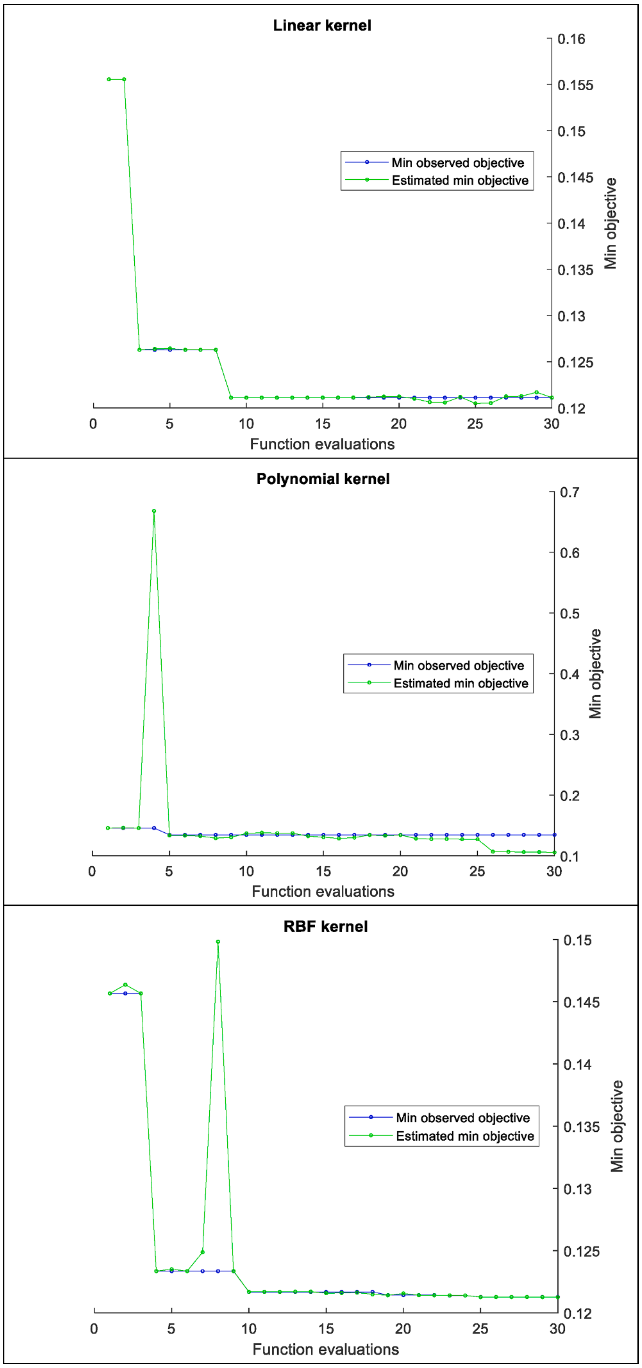

Fig. 3. Examples of plots of the minimum objective function against the number of function evaluations following Bayesian optimization for each type of kernel: linear, polynomial, and radial basis function (RBF) kernel. Examples are from Aragon change in volume data.

focusing on the forecasting next-day variation in volume of transactions in cryptocurrency markets. The secondary goal is to describe complexity in such data by means of three different statistical mechanics measures. Hence, the current work is the first to tackle these topics; especially the first one.

Indeed, we examined the performance of the optimized support vector regression in the task of forecasting next-day and next-week variation in volume of transactions of a large set of cryptocurrencies under three different kernels, thirty digital assets in total. Hence, ninety forecasting experiments have been conducted. Unlike the classical ordinary lest squares, the SVR was used in our study thanks to its ability to apply the structural risk minimization principle to minimize an upper bound on the generalization error rather than implementing the empirical risk minimization principle to minimize the training error, guarantee to achieve the global optimum, capability to use kernel for nonlinear mapping of the data, it is free of standard statistical assumptions, and can provide good generalization results even the data sample is small (Vapnik et al., 1996). It is worth mentioning that the SVR is robust when data sample is small and flexible as it uses various kernels. However, optimal values of the parameters of the kernels should be optimally determined. In addition, the SVR requires a long training time for large samples.

Table 1
obtained performance metrics.

	RMSE	MAE	RMSE	MAE
	Daily	Daily	Weekly	Weekly
SVR-BO with linear kernel	0.2589 ± 0.1438	0.2401 ± 0.1327	0.3501 ± 0.1531	0.3413 ± 0.1198
SVR-BO with polynomial kernel	0.2177 ± 0.1546	0.2036 ± 0.1435	**0.1045 ± 0.1001**	**0.1009 ± 0.1170**
SVR-BO with RBF kernel	**0.2111 ± 0.1504**	**0.2013 ± 0.1422**	0.1101 ± 0.1320	0.1002 ± 0.1301
ARIMA process	0.4787 ± 0.1791	0.4387 ± 0.1135	0.8901 ± 0.3711	0.8876 ± 0.7172
Lasso regression	0.4340 ± 0.1703	0.4251 ± 0.1641	0.8139 ± 0.3852	0.8100 ± 0.5287
Gaussian regression	0.4051 ± 0.1611	0.4003 ± 0.1587	0.7015 ± 0.3321	0.7001 ± 0.3901

The choice of the relatively small time period was motivated by forming a large number of cryptocurrencies with significant number of transactions and price movements. In this regard, the SVR is an appropriate choice as it is capable to provide good generalization even from small data and to achieve global optima (Vapnik et al., 1996). Besides, by performing simulations on thirty markets for each kernel function we expect being able to draw general and robust conclusions.

For each experiment, the Bayesian optimization was adopted to find optimal parameters of the SVR under each different kernel. Indeed, theoretically speaking, Bayesian optimization is fast to get to the optimal set of parameters and bring better generalization performance on the test set (Gelbart et al., 2014). For instance, since the BO method naturally requires less iterations to get to the optimal set of hyperparameter values, it considers only areas of the parameter space based on beliefs used to choose a prior probability distribution for the model parameters. Bring in mind that we focused only on optimizing SVR by BO and conducted comparisons under different kernels and the comparison of BO with other optimization methods is out of scope of the current work.

Besides, nonlinear analysis based on measurement of three different complexity measures have been applied to each time series for good characterization of their nonlinear dynamics. For instance, detrended fluctuation analysis, sample entropy, and the largest Lyapunov exponent based on the method of Rosenstein were respectively employed to capture long-memory, randomness, and chaos in each volume data. These complexity measures are suitable to describe nonlinear dynamics in data with no prior assumptions. This is the first paper to examine nonlinear dynamics in volume variations of cryptocurrencies, to the best of our knowledge.

In sum, the results from ninety experiments can be summarized as follows. First, the outcomes from nonlinear analyses show that changes in volume of transactions are self-similar, random, and chaotic. Hence, there is a potential to predict volume data of cryptocurrency markets. Second, we concluded from our ninety experiments that Bayesian optimization method is fast; especially when used to tune parameters of the RBF kernel. Third, we found that SVR with RFB kernel outperformed all models when used to predict next-day trading volume while SVR with polynomial kernel outperformed all other models when used to predict next-week trading volume. This finding can be explained by the fact that RBF kernel helped capturing local variations in daily trading volume while polynomial kernel helped capturing general trend in weekly trading volume. Fourth, all SVR models outperformed statistical benchmark models (ARIMA, Lasso regression, Gaussian regression) on both daily and weekly data. Fifth, the Gaussian regression model performed better than ARIMA process and Lasso regression on both daily and weekely data.

For future work, the current study will be extended to a classification problem to predict next move direction in volume of transactions.

CRediT authorship contribution statement

Salim Lahmiri: Conceptualization, Methodology, Software, Data curation, Writing – original draft. **Stelios Bekiros:** Conceptualization, Methodology, Software, Data curation, Writing – original draft. **Frank Bezzina:** Conceptualization, Methodology, Software, Data curation, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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