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THE PREDICTIVE MODELING OF THE FINANCIAL RISK OF CRYPTOCURRENCIES

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Abstract

As the bitcoin community has grown rapidly, volatility is the only parameter that determines the price of a bitcoin and is not directly observable on the market. In this research, we apply a model of intelligent agent-based system to predict the trading price of bitcoins using data from listed cryptocurrencies like bitcoins on the CoinMarketCap. The main contribution of this paper is to show empirically that the price prediction model for bitcoins based on neural networks and the volatility prediction model based on technical analysis, form a decision support subsystem. The positive aspects of decentralization, anonymity, transparency, transaction speed and low costs, clearly show why Bitcoin is becoming more popular and future plans include generating similar bridges for other blockchains, such as Tron, EOS or Binance Chain.

Keywords: Cryptocurrencies; Bitcoin; Volatility; Artificial Neural Networks; Intelligent Systems; Exchange Risks

1. Introduction

Simultaneously with the arrival of the pandemic in Europe and the restrictions it brought, the cryptocurrency market - led by bitcoin - began to grow in March 2020 and did not stop until the first days of January, when it reached an all-time high. of $ 41,962 (CoinMarketCap 2021). With a wave of new money entering the market, the debates around cryptocurrencies have rekindled, and the role of bitcoin is once again under scrutiny, as well as the financial education of those who adhere to this phenomenon (Conlon et al. 2020; Bons et al. 2020). With analysts projecting more than $ 700 Bln on Bitcoin by the end of 2021, financial institutions are gradually building their own encryption portfolios (CoinMarketCap 2021).

In this world of cryptocurrencies, bitcoin acts as a gold standard (Baek and Elbeck 2015; Marella et al. 2020; Bouri et al. 2020; Yermack 2015). Cryptocurrency can also be used for currency speculation, the value of a Bitcoin fluctuating at least as much on digital currency exchanges, which claims the need for predictability of trading prices (Dyhrberg et al. 2018; Ma et al. 2018; Mikhaylov 2020; Arias-Oliva et al. 2021; Tasca et al. 2018). This implies that the Bitcoin community must be prepared to protect the system from several illicit activities on market (Park and Jun 2020; Roper et al. 2011; Syed et al. 2019).

The emergence of the blockchain technology that underlies bitcoin has transformed many aspects in a positive way because it allows secure transactions, greater efficiency and can reduce the need for intermediaries (Sladić et al. 2021; Alt 2020; Ali et al. 2020). Although technology offers many advantages and solves many problems, it cannot solve all problems. In other words, blockchain technology is the beginning of a new digital age, an era that can solve many of the problems we face or an era that can take us even further away from normalcy.

At the same time, in the case of cybercriminals, the modes of operation have diversified with their improvement and the identification of new methods of fraud (Brauneis and Mestel 2018; Ghabri et al. 2020; Jha and Baur 2020). Cloning of official websites where cryptocurrencies are traded as a way to counterfeit electronic money and deceive by forcing its users to transfer money is becoming more common. Thus, as long as the problems of credibility and the inflation rate are eliminated, the specialized studies present arguments regarding the possibility that Bitcoin can coexist as a modern payment method but with huge monitoring costs due to the size of the data (Martinazzi et al. 2020; Hoang et al. 2020).

In this context, every transaction that takes place in the Bitcoin network is registered in the blockchain, there is an increasing need to take important steps towards creating models to predict the price of cryptocurrencies quota and values using computational intelligence methods (Nasir et al. 2019; Conrad 2018; Chuen 2015). In practical applications, this parameter must be estimated given that the evolution of the price of the underlying asset is assimilated to a certain distribution (Balcilar et al. 2017; Lischke and Fabian 2016; Kroll et al. 2013; Chan et al. 2019). Moreover, empirical studies that took into account the evolution of the dispersion of the price of underlying assets between two consecutive closures and between the close before the weekend and the first trading day following this period led to the conclusion that much volatility is the result of the trading process (Trucíos 2019; Hamid 2015; Wang 2003).

The tendency of volatility to return to a long-term characteristic value contained in the above model may be one of the explanations for the maturity dependence of the default volatility (Wang 2003; Palos-Sanchez et al. 2021; Sun et al. 2018; Livieris et al. 2021). However, an important result for options theory refers to the way in which the probability distribution can be transformed into a more convenient one, which eliminates the risk associated with a bitcoin, leaving the structure of volatility intact (Yang et al. 2020; Dodd and Gilbert 2016). Meanwhile, according with Conrad et al. (2018) in the study of financial time series are used the ARCH/GARCH models. Furthermore, the level of risk exposure of each company must incorporate its own assessment of the losses they may incur in the event of unfavorable market developments (Sun et al. 2018; Dodd and Gilbert 2016). Trading models and techniques must be seen as tools that can provide an informed manager with useful insights, so they are indispensable in an increasingly integrated and sophisticated market (Wang 2003; Dodd and Gilbert 2016; Cernazanu 2008; Cebrián-Hernández and Jiménez-Rodríguez 2021).

Based on previous research, the objective of this study is to create a subsystem of decision assistance on the trading segment of bitcoins based on classical technical analysis, supplemented with mechanisms for identifying, collecting, structuring and updating data, with mechanisms for analyzing the main indicators related to price and volatility (Cuc 2017). As a result, each trading of bitcoins signal is automatically analyzed for profitability. This analysis simulates the trading signal using the real price of Bitcoin time series. According with the results, this simulated

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trading makes an analysis of the manner in which each transaction is done both based on trading or on one-day aggregation.

From a practical perspective, the topicality of the present research study is due to the continuous evolution of the techniques by which coins are protected, but by which they can also be counterfeited – there is some research on blockchain-enabled and blockchain-induced applications in cryptocurrency trading. Another reason would be the need to implement a unitary package of elements so that the person handling the banknote is able to compare authenticity in real time and specially to know these elements in advance.

The remainder of the paper is organized as follows: Section 2 presents a brief literature reviews regarding the agent-based system implementation for the minimization of the trading risk. Section 3 provides the theoretical model followed by the illustration of estimation methodology. Section 4 analyses the empirical results and discussions implications. Section 5 drives conclusions.

2. Theoretical background

As already presented in the literature, volatility is often used to quantify the risk of a cryptocurrency in a given period of time and represents the variation (or, alternatively, the standard deviation) of the instrument value's alteration in this time horizon (Livieris et al. 2021; Bordini et al. 2006; Tse and Tsui, 2002; Fernández-Villaverde and Sanches 2018). Therefore, volatility modelling and prediction become an important task on markets, being motivated by the desire to minimize the trading risk.

As a measure of minimizing the incertitude, volatility becomes a key issue for any investment decision and portfolio management, as well as for the risk evaluation, for the bitcoins' pricing, for the derived securities and options' pricing (Gao et al. 2016; Haykin 2009; Riganti et al. 2012; Sarma 2009; Georgescu 2011). Certain types of cryptocurrencies commonly show high and low volatility periods (the so-called volatility clustering). During these periods of time the price variations are very frequent and they have a high amplitude (an extreme case is a market incident – or market bubble), while during other periods they might seem to have a low amplitude for a longer period of time (Georgescu 2011; Arias-Oliva et al. 2021; Brauneis and Mestel 2018; Nasir et al. 2019; Livieris et al. 2021). The extremely volatile markets can be exploited for speculative trading actions and represent good but risky opportunities for gains (Georgescu 2011; Gao et. al. 2016; Weigend 2018).

Numerous studies found volatility is extremely important in the bitcoins' pricing (Hamid 2015; Dodd and Gilbert 2016). According to most of the theories referring to the bitcoin's pricing, the risk premium is determined by the conditioned covariance between the asset's future returns and one or more reference portfolios (e.g. market portfolio or consumption growth rate). Investors and portfolio managers have certain risk levels that they can bear (Georgescu 2011; Hamid 2015; Gao et al. 2016).

Trucíos (2019) and Hamid (2015) believe that a good prognosis of the bitcoin's prices volatility during the investments holding period is a good starting point for evaluating the investments risk, but the high scale failures of the risk evaluation are very hazardous and may generate financial crises. Thus, the accuracy of volatility prediction is essential in pricing the derivative instruments, where the uncertainty associated with the future price of the bitcoin a major factor for the prices of the derivative instruments (Georgescu 2011). Actually, this makes possible the direct trading of the volatility, by using the derivative instruments such as the options, whose trading volume has increased four times in only a few years before the latest financial crisis (Yang et al. 2020).

Other authors found that, in order to establish an option's price, the volatility of the basic asset until the options expiration needs to be known (Conrad et al. 2018; Cebrián-Hernández and Jiménez-Rodríguez 2021). As a matter of fact, the market convention is to express the options' prices in volatility units, favoring a clear specification of the volatility's quantification in the contracts containing derivative instruments, provided that the predictions are highly accurate (Georgescu 2011). Nevertheless, volatility is not the same thing as the risk, being defined as an information vehicle which can be exploited for speculative trading. The traders can make high gains through volatile markets, in case of a short time entering with peak prices selling and low prices buying, in which situation the gains are proportional to the volatility, provided the prediction is as accurate as possible. Various models are applied on the developed markets volatility estimation, but risk portfolio management of investments has led to the need to try to model it using intelligent agents (Cernazanu 2008; Bordini et al. 2006; Haykin 2009).

Note that the critical module of agent has a performance standard usually implemented in the design stage that enables the evaluation of the action's results depending on the purpose, determining the knowledge to be provided to the learning module. If the performance standard is not set, the agent will adjust it for its behavior improvement. The agent's behavior can be improved by learning. Learning can be: supervised, unsupervised, reinforcement, online, offline, centralized and decentralized. The agent's knowledge base is updated following the learning process (Riganti et al. 2012; Sarma 2009; Patel et al. 2020).

Other studies focused on the most largely spread neural networks of the feed-forward type and which proved to be real functions universal approximates are the multilayer perceptron (MLP), having one or more hidden layers (Dodd and Gilbert 2016; Demuth et al. 2014; Alberola et al. 2013, Cuc 2017).

Supporting this view, the genetic algorithms can be combined with neural networks in order to improve their performance by finding the optimal parameters or in order to be used in the post processing optimization stage (Tse and Tsui 2002; Weigend 2018; Cuc 2017). The network must be trained without regularization, because it will increase the error. This causes predictors to remain stable and generally give rise to more robust models.

According to Haykin (2009), the main characteristics of a neural network are: nonlinearity, adaptability and parallelism. To define a neural network, we must define a structure and a rule of learning. On the other hand, the reason why the forecasting capacity of a network is affected by the series trend emerges immediately from the need to normalize the network inputs (Montgomery et al. 2015). However, the usefulness of a neural model lies primarily in its consistency, even if its performance is not so good. Constantly looking for the simplest model to represent a series of time as efficiently as possible, it is finally necessary to reach a balance between complexity and accuracy.

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Even so, multi-agent systems are systems consisting of groups of agents acting for the achievement of a common purpose. In order to do this, the agents making up a system of agents interact and work together for the achievement of the common task. As a rule, multi-agent systems are involved in solving specific problems with a very high complexity in order to be solved by only one agent.

3. Research methodology

Data used were extracted for listed cryptocurrencies like bitcoins on the CoinMarketCap (2020) and the analysis interval comprises a period between 2017 and 2020, with an aggregate of 1460 recordings for the data series of the variable – daily closing price.

Figure 1. Daily price of Bitcoin (BTC) from 1 January 2017 to 31 December 2020.

From the analyzed data one notices that is present the volatility clustering phenomenon (the periods of high and low volatility are persistent; the periods of volatility calmness and turbulence tend to group together); bitcoin daily average returns is equal to the yearly returns divided to the number of trading days; the daily returns distribution is leptokurtic (fat tail) and bitcoin returns display a certain asymmetry.

According to previous studies (Georgescu 2011, Cuc 2017), the optimal model is from the $ARMA(n,m)/GARCH(p,q)$ class, which highlights the two main features of the returns series: leptokurtic distribution and volatility clustering.

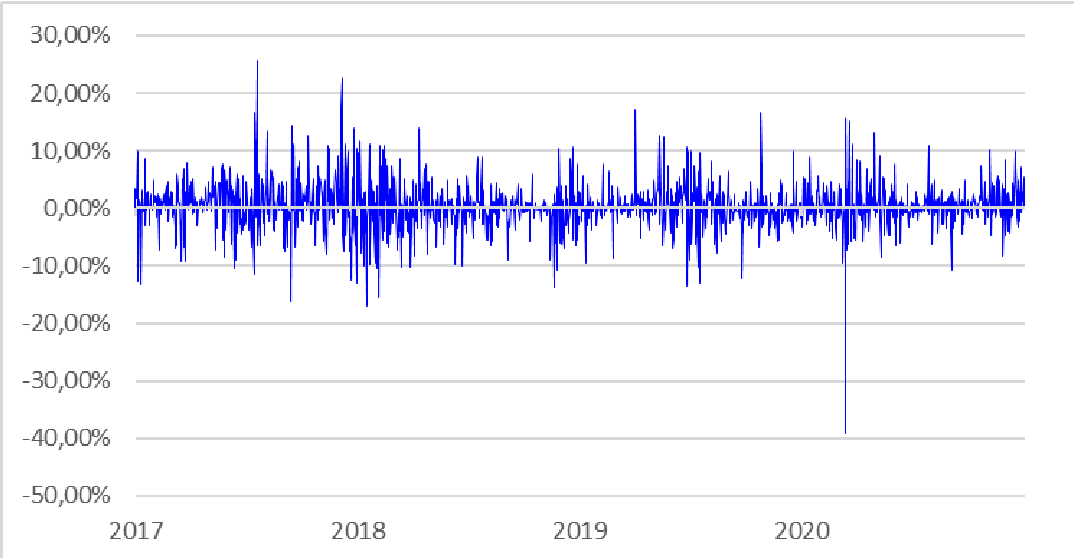

Figure 2 – Daily returns of Bitcoin (BTC) from 1 January 2017 to 31 December 2020

From the relation:

$$r_t = \ln(P_t) - \ln(P_{t-1}) = \ln\left(\frac{P_t}{P_{t-1}}\right) \Rightarrow E(r_t) = \mu \quad (1)$$

,

that could depend of past information

$I_{t-1} = \{r_{t-1}, r_{t-2}, ...\}$, data from previous observations $(r_{t-1}, r_{t-2}, \ldots)$ previous exogenous vectors or variables $x_{t-1}, x_{t-2}, \ldots$ or previous innovations $\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots$ provides the characterization given by $ARMA(n,m)$ for average daily returns

$$r_t = \mu + \sum_{i=1}^{n} a_i \, r_{t-i} + \varepsilon_t + \sum_{j=1}^{m} m_j \, \varepsilon_{t-j} \quad (2)$$

,

If the relation (1) is independent of the set of information from the past
$I_{t-1} = \{r_{t-1}, r_{t-2}, ...\}$,

the reductions $r_t = \varepsilon_t \; r_t = \mu + \varepsilon_t$ or, take place

where $\varepsilon_t = \sigma_t \, e_t$ represent the innovations of the average returns series of and they completely characterize the volatility clustering phenomenon.

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The returns volatility will be modelled by a $GARCH(p,q)$ model:

$$\sigma_t^2 = k + \sum_{i=1}^{p} G_i \sigma_{t-i}^2 + \sum_{j=1}^{q} A_j \varepsilon_{t-j}^2 , \tag{3}$$

A generation mechanism for innovations $\{\varepsilon_t\}$ $\varepsilon_t = \sigma_t e_t$ is where $\sigma_t^2 = Var[\varepsilon_t | I_{t-1}] = E[\varepsilon_t{}^2 | I_{t-1}]$ is the variance conditioned by the innovations ε_t and r_t where $e_t = \varepsilon_t / \sigma_t$ define the standardized innovations, i.e $e_t \sim i.i.d.N(0,1)$.

The restrictions imposed to the conditioned variance parameters are:

(i): $\sum_{j=1}^{p} G_j + \sum_{i=1}^{q} A_i < 1$ (stationarity)

(ii): $k \geq 0$, $G_j \geq 0$, $j = 1, \dots, p$; $A_i \geq 0$, $i = 0, 1, \dots, q$ (nonegativity). (4)

The next step is testing data series for underlying volatility clustering and $GARCH$ effect. The test is based on the local equivalence between $GARCH(p,q)$ and $ARCH(p+q)$ models and analyzes the null hypothesis:

The residual series $\{\varepsilon_t\}$ does not have conditional heteroscedasticity as against the alternative that the model $ARCH(L)$:

$$\hat{\varepsilon}_t^2 = \phi_0 + \phi_1 \hat{\varepsilon}_{t-1}^2 + \ldots + \phi_L \hat{\varepsilon}_{t-L}^2 + \nu_t , \tag{5}$$

describes the series having at least $\phi_k \neq 0,\ k = \overline{0, L}$.

Afterwards, we will use the maximum probability calculation (ML) to estimate the returns mean and their volatility.

ARMA (0,0): $r_t = \mu + \varepsilon_t$, unde $\varepsilon_t = \sigma_t e_t$ și $e_t \sim i.i.d.N(0,1)$

GARCH (1, 1): $\sigma_t^2 = k + G_1 \sigma_{t-1}^2 + A_1 \varepsilon_{t-1}^2$, where initial iteration is $\sigma_1^2 = \dfrac{k}{1 - G_1 - A_1}$,

We define Log-probability notion of r_t as equal to Log-density of r_t and we calculate $LLF(r_t, k, G_1, A_1, \mu)$ after the resulted formula:

$$LLF(r_t, k, G_1, A_1, \mu) = \sum_{t=1}^{n} \log\left[\left(\frac{1}{\sqrt{2\pi}} \exp\left(\frac{-(r_t - \mu)^2}{2\sigma_t{}^2}\right)\right)\right], \text{ where } \sigma_1^2 = \frac{k}{1 - G_1 - A_1} \tag{6}$$

For calculated parameters $k,\ G_1,\ A_1,\ \mu$ we calculate

$$\max_{k, G_1, A_1, \mu} LLF(r_t, k, G_1, A_1, \mu) = \max \sum_{t=1}^{n} \log\left[\frac{1}{\sqrt{2\pi}} \exp\left(\frac{-(r_t - \mu)^2}{2\sigma_t{}^2}\right)\right]$$

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This maximum is reached at the maximum point $\left(G_1^{\max}, A_1^{\max}\right)$ and the maximum value is $LLF\left(r_t, k, G_1^{\max}, A_1^{\max}, \mu\right)$

Controllability of volatility risk for financial assets followed by the underlying asset starts from the observation that the price change follows a continuous process, the result generated being distributed normally.

4. Results and Discussion

Following the proposed model and data presented above, the Figure 1 and 2 shows the implications of the clustered volatilities can be quantitatively characterized by the autocorrelation functions (ACF) and the partial autocorrelation functions for returns r_t samples from Figure 3 as well as for r_t^2 in Figure 4

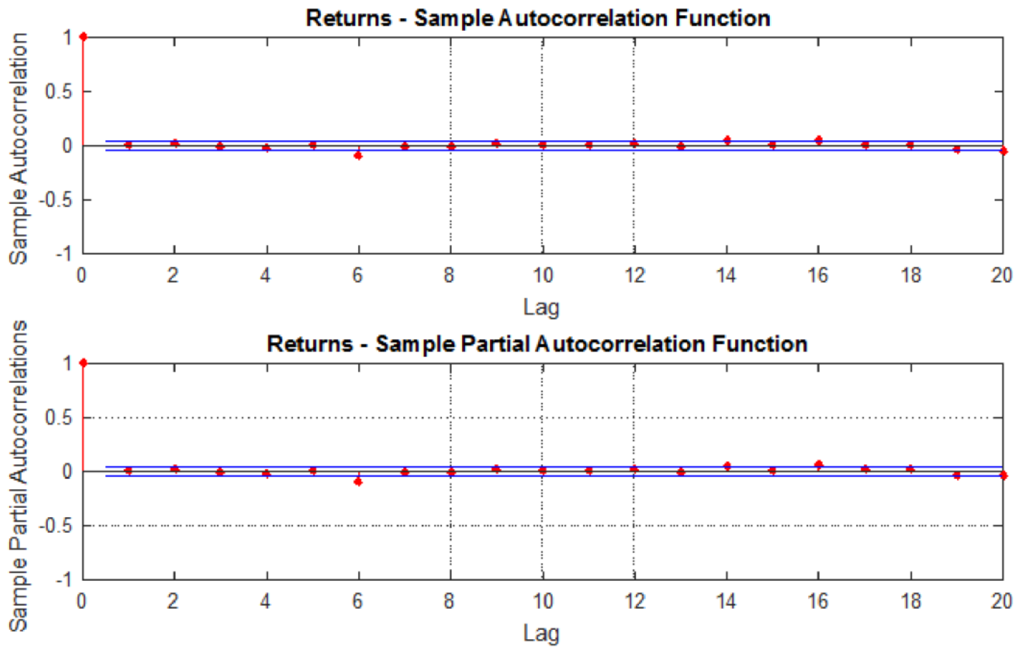

Figure 3. Graph of the observed returns r_t sample (Lag =1 - 20) correlation.

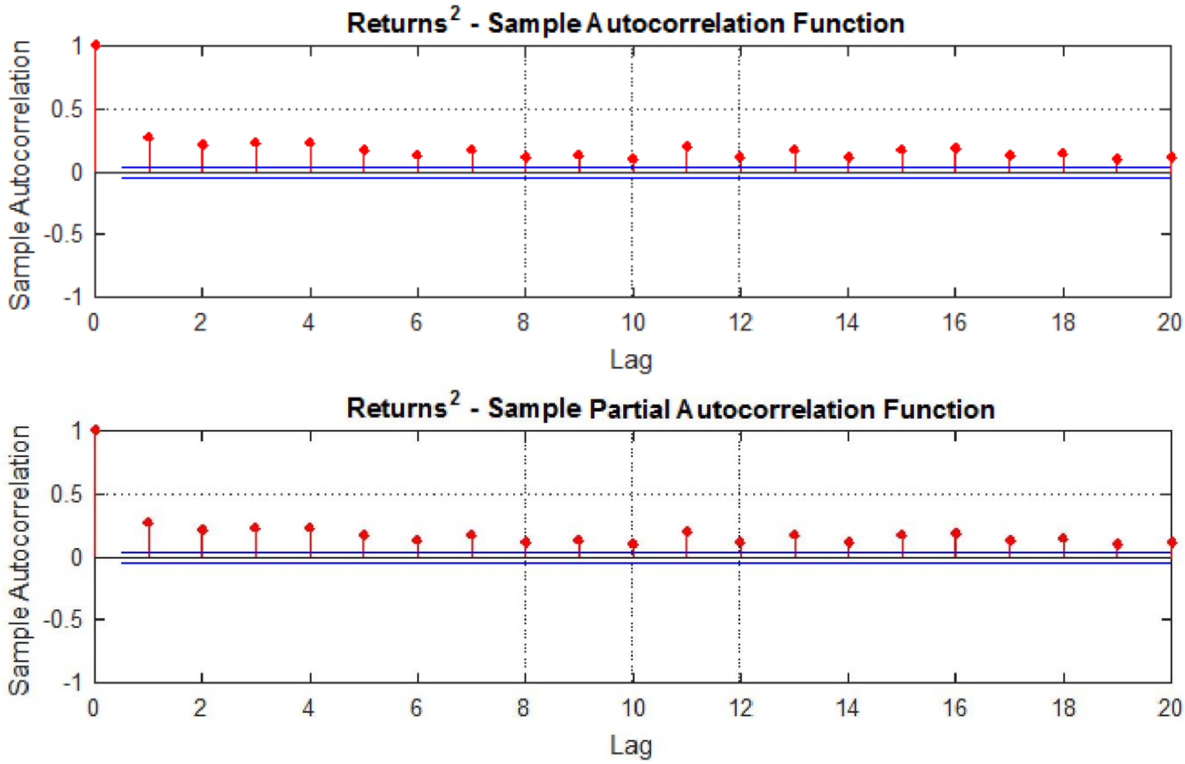

Figure 4. Graph of the observed squared returns r_t^2 sample (Lag =1 - 20) correlation.

A first conclusion that can be drawn is that the returns are mostly uncorrelated in the level, but squared correlated. Both correlation functions were calculated up to a $K=20$ disparity and show a typical behaviour: while autocorrelation is low in the basic returns' series, the volatility series (squared returns) show the persistency corresponding to a high autocorrelation level, long-term time scale.

For the bitcoin data series analyzed, we testing ($K=20$):

$$H_0 : \rho_1 = ... = \rho_{20} = 0$$
$$H_1 : \exists \rho_j \neq 0 \quad (j = 1,2...,K)$$

For L = 2, N=1640, T=1638 and GARCH (1,1) we will have: R^2 = 0.12637, LP = (T-L) $\cdot R^2$ = (1640-2) 0.12637 = 206.9941 > χ_{20}^2 (2) = 31.41 and 5% level = 6.1023, so we will reject hypothesis H_0 for the 5% level.

The conclusion of the test is that the returns series meant shows clustered volatility, previously determined, as well as the GARCH effect. Further using the calculation of the maximum probability (ML) to estimate the average yields and their volatility we obtain the results presented in Table 1.

Table 1. The results of estimates of average returns and their volatility.

Parameter	Estimation	Standard **error**	t statistics
k	0.0000769	0.0002534	8.8883500
G_1	0.7463166	0.0117543	67.6353500
A_1	0.2164427	0.0122587	17.8829500
μ	0.0003483	0.0002998	1.13233610

Moreover, Figure 5 representing this maximum for the data series corresponding to bitcoin.

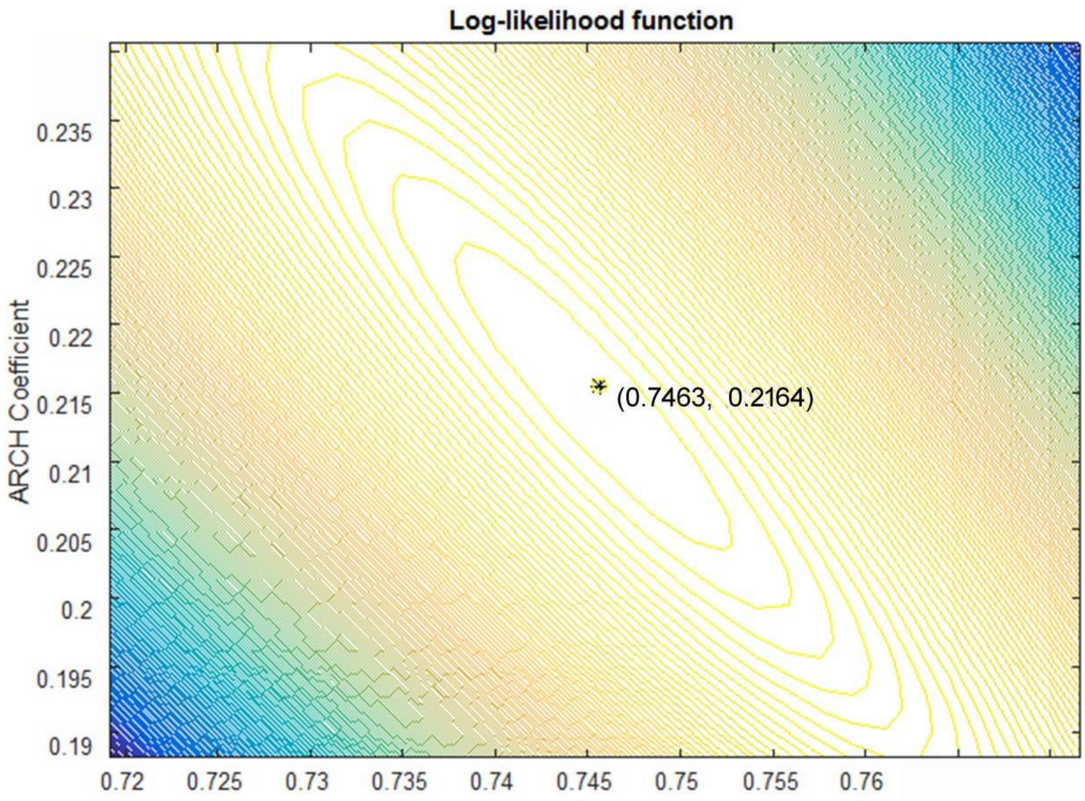

Figure 5. Graph of observed the maximum point $\left(G_1^{\max}, A_1^{\max}\right)$

We notice that $\left(G_1^{\max}, A_1^{\max}\right)=(0.7463, 0.2164)$, and the maximum value reached in this point is $LLF\left(r_t, k, G_1^{\max}, A_1^{\max}, \mu\right)=6187.6951$ (Figure 6).

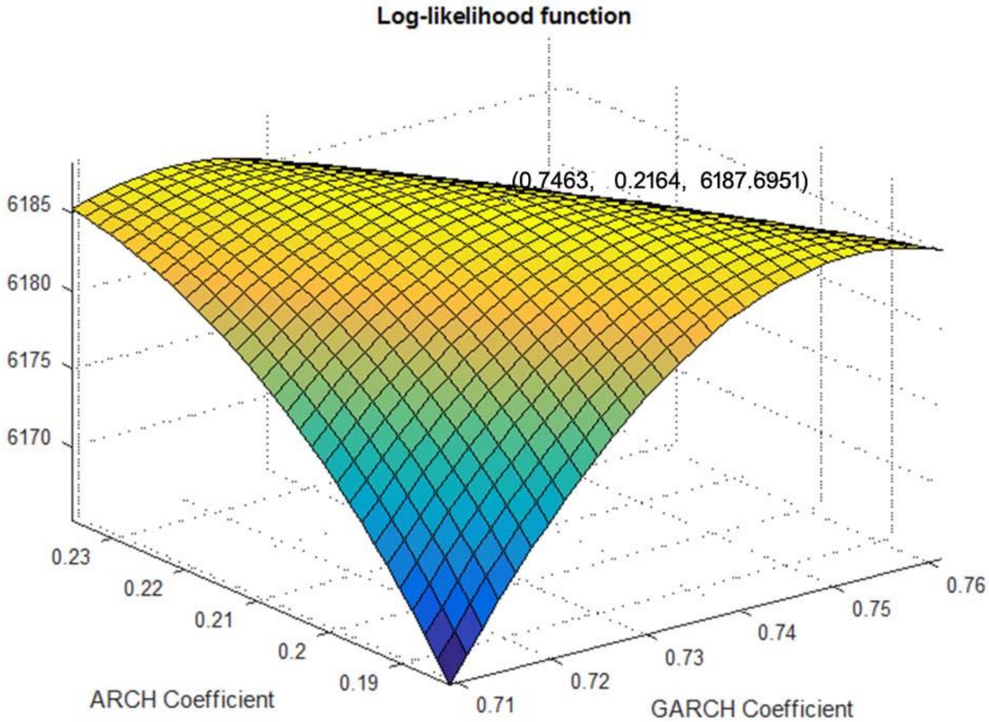

Figure 3. Graph of observed the maximum value for $LLF\left(r_t\ ,k,G_1^{\max},\ A_1^{\max},\ \mu\right)=6187.6951$

The unconditioned variance of innovations ε_t will be given by:

$$\hat{\sigma}_{\varepsilon}^{2}=\hat{\mathrm{var}}\left[\varepsilon_t\right]=\frac{k}{1-G_1^{\max}-A_1^{\max}}=0.0020615, \qquad (7)$$

Correlating this with the fact that $G_1^{\max}+A_1^{\max}=0.9627$ the conclusion is that volatility is strongly persistent for bitcoin.

The advantages of using normal distribution to control the risks of bitcoin volatility in this model are obvious. Basically, the complete distribution of the price of the underlying bitcoin and of the probabilities of achieving the values generated can be generated depending on the average price change and their standard deviation. In addition, the use of lognormal distribution has the advantage that a variable thus distributed can only take positive values, a realistic assumption in the case of the price of bitcoin.

On top of that, used in the training process for error monitoring, the validation data tables will be processed to generate the learning stopping decision so as to avoid overfitting. The error associated to the subset containing the training data decreases during the initial epoch, simultaneously with the error reduction from the validation data set. The error reduction from the validation data set starts vanishing and is subsequently followed by the trend's reverse at the moment when the network starts overfitting.

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When the validation data error increases for a limited iterations interval, the training is stopped and the resulted weights are considered optimal, thus obtaining the optimum model in relation to the error established by the upper layer. In fact, the error for the testing data set provides an enough good estimation of the generalized error, being used, for this reason, to compare various models.

In the light of the results of this study, the fact that Blockchain technology is not a valid universal "remedy" must be taken into account, because it still has a long way to go until it is fully integrated into every business process. However, it is worth considering the benefit of a debate on the practical and legal implications of Blockchain technology in major organizations around the world. As an extension of this study, the following question remains: how might the use of prediction models influence future transactions?

5. Conclusions

One important and extremely present phenomenon of our current world is called bitcoin and it is a decentralized electronic payment system and digital currency cryptocurrency, created to ensure investment protection and free financing of business without resorting to financial institutions, outside any constraints and regulations. An advantage that the bitcoin gives to the system is considered to be the fact that at some point, out of the extremely complex monetary circuit, all types of currency would disappear and also it is possible that counterfeit currency would become a thing of the past as well.

The development of the financial environment generates higher and more expensive risks in terms of coverage. According to the present survey, subjects involved in the use of risk assessment techniques by analyzing prices and volatility can ensure a more realistic perception of the value of a bitcoin. In view of obtaining the models which were encapsulated in the prediction agents, the parsimony principle was considered, according to which a model has to include what is required for modelling, and nothing more. The violation of this principle results in excessive adjustment of a model, a phenomenon called overfitting. This models are either too flexible or excessively complex, with a disproportionate number of parameters in relation to the number of processed parameters and to the number of analyzed observations.

Along the same line of thinking, it should be noted when training the neural networks, we have envisaged to obtain a model with optimal generalization performances. However, one has to take into account that a standard architecture neural network of multilayer perceptron type is overfitting-prone. In order to counteract this native tendency, we have applied the early stopping of the training process. The early stopping process implies data splitting into three subsets: training, validation and testing. The learning data used for training (gradient and network weights) are the most consistent part of the available data.

This empirical analysis also highlights that the agent built by the encapsulation of model will be an intelligent one because it trains daily, resulting, at the end of the day, in a new agent version for each issuer it will train for. As results shown, the model chosen to make the prediction must meet the principle of parsimony, the cost of resources allocated for running neural networks with many neurons and many layers, as well as the large number of training epochs, not desirable, relative to the goal model, to have a small error to perform transactions or to ensure a price alert for the predicted values.

At the end of each trading day, the specific predictive model is generated and included in the agent that will use the model in order to make predictions for the next trading day. The model thus generated recreates itself daily, by self-training with the current day's data. In off line, the coordinating agent assumes the updating data of the predictive and intelligent models through the interface agent and transfers them to the suitable agents so as to be used during the next trading session.

The partial derivative equation included in modelling and predicting the volatility of bitcoin prices using intelligent agent systems, used in the evaluation of options can also be obtained by an alternative technique, which involves building a portfolio consisting of risk-free fixed income shares, options and securities that do not require an initial investment or additional funds during the life of the option.

Finally, another natural development direction will be the computing power scaling for distributed systems in BIG DATA environment, specific to neural networks, alongside the creation of models proper to each activity sector. The scaling thus achieved would enable the increase of profitability for all issuers on the exchange market, to which the state is a holder, beside an efficient and effective control of their trading processes.

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