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Can artificial intelligence enhance the Bitcoin bonanza☆

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Abstract

This paper aims to investigate how Machine Learning (ML) techniques perform in the prediction of cryptocurrency prices. We answer if Support Vector Machines (SVM) and Artificial Neural Networks (ANN) based strategies can generate abnormal risk-adjusted returns when applied to Bitcoin, the largest decentralized digital currency in terms of market capitalization. Findings indicate that traders are able to earn conservative returns on the risk adjusted basis, even accounting for transaction costs, when using SVM. Furthermore, the study suggests that ANN can explore short run informational inefficiencies to generate abnormal profits, being able to beat even buy-and-hold during strong bull trends.

JEL Code: G11; G15; G17

Keywords: Bitcoins; Machine learning (ML); Artificial neural network (ANN); Support vector machine regression (SVM)

1. Introduction

Cryptocurrencies are attracting the attention of the media due to their jaw-dropping performance and rapid growth in recent years. Many individuals are fascinated by such financial instruments providing possibility of generating quick wealth through rapid price appreciation albeit the excessive volatility and high risk. In December 12th 2017, the price of Bitcoins peaked at USD 17,600, up by 1,660 percent since the beginning of the year. In fact, Bitcoins are speculative in nature.[15]

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There is a growing academic literature on virtual currencies such as Bitcoins, the largest digital currency in terms of market capitalization, as well as alternative cryptocurrencies (e.g. Ethereum, Ripple and Litecoin). Particularly, Bitcoins are traded in several exchanges (e.g. Bitstamp, BTC-e, Coinbase, Bitfinex, and Cryptcy), and the market is unregulated.

It is worth noting that Bitcoin and cryptocurrencies are classified as commodities according to the Commodities Futures Trading Commission (CFTC). However, they cannot serve as a legal tender which make them different from fiat currencies. In a recent study,Klein et al.[62] show that Bitcoins does not behave similarly to gold and silver, especially in market turmoil. Similarly, Baur et al.[11] show that Bitcoin are different from them and US dollar in terms of return and risk characteristics. Also, Cryptocurrencies are not connected to other financial assets.[35]

Kristoufek[64], Tiwari et al.[100], Khuntia and Pattanayak[59], Al-Yahyaee et al.[1], Urquhart[102] and Bariviera et al.[8] points out the key aspects of Bitcoin inefficiency, in the sense of Efficient Market Hypothesis (EMH),[45] which states the prices contains all relevant information available. There are smooth versions of the EMH, but a major implication is that prices cannot be predicted by past information.

Bariviera et al.[8] study, through the methodology suggested in Hurst[55]; long memory at time series and obtain that Bitcoin market is clearly inefficient. Also, Urquhart[102] analyses autocorrelation and unit root tests for Bitcoin data and finds out that it does not come from a random walk process. However, according the author, tests with two sub samples within the whole sample shows that the underlying process for the second half of the data has stronger memory than the first half. This finding may indicate this cryptocurrency markets tends to become more efficient over time, as suggested by Souza et al.[95] and Chong et al.[30] for stock market.

Similarly to global financial assets, Bitcoin constitutes a safe investment option during global financial stress, as suggested by Bouri et al.[16] Various specific factors, including the international inefficiency of the Bitcoin market may explain Bitcoin's diversification feature.

According to EMH, you cannot beat the market consistently on a risk-adjusted basis using historical information. Other studies[24,33,104] are pointing to the notion that capital markets are not always efficient and efficiency could be time-varying which is consistent with the Adaptive Market Hypothesis (AMH).[71] According to AMH, investors are able to beat the market in certain episodes of inefficiency and temporary irrationality. Therefore, they should be consistently searching for strategies that work during these periods as such opportunities come and go.

Since Cryptocurrencies are relatively new, many investors and researchers try to investigate their properties and profit potential. In this sense, Bal (2015, pp. 269−270)[5] arguments that Bitcoin weakly satisfies medium of exchange property, once it is accepted in a just few venues as a payment mechanism. This fact together with the high volatility of the Bitcoin price cannot guarantee the property of unit of account as the author highlights.

One of the strands of the emerging literature on Bitcoins is related to the informational efficiency in its weak-form (i.e. can we use historical information to better predict the future movements?). For example, Urquhart[102] finds that Bitcoins were informationally inefficient during the period 2010−2016, by using six econometric techniques (i.e. Ljung-Box, Runs, Bartels, Automatic Variance Ratio (AVR), R/S Hurst and BSD test). However, the author finds some evidence of improving efficiency when reapplying the tests on the recent period during from 2013 to 2016. This improvement in efficiency could be attributed to more traders and higher trading volume.

In contrast, Nadarajah and Chu[75] indicate that Bitcoins are informationally efficient when using power transformation to the data under investigation. However, both studies do not move into the following step of testing whether or not investors can benefit from such inefficiencies (if any). Thus, we extend and complement their work by applying artificial intelligence techniques, more specifically, Support Vector Machines (SVM) and Artificial Neural Networks (ANN), on Bitcoins to investigate the possibility of devising strategies to generate abnormal profits and take advantage of predictabilities.

Although Bitcoin prices have substantially increased in the last years,[6] short-term fluctuations preclude a steady uptrend. In this context, the objective of the study is to analyse whether artificial intelligence can help capture short term-trends and lead to opportunities of obtaining abnormal returns, even when there is clear middle or long term one-directional behaviour in the price of an asset. Therefore, in this situation, we would hope that the trading strategy could lead to higher risk-adjusted return in comparison to a buy-and-hold strategy.

Financial time series prediction is a challenging task, considering the noise and amount of information available for traders.[65,89] The markets are dynamic, non-linear, chaotic and noisy,[112] subject to economic variables, enterprise policies, politics, news and psychology of investors.[27] However, its prediction could lead to profitable trading opportunities and risk management possibilities.

Traditional statistical techniques have been applied to securities prices prediction, such as Kalman filters, Moving Averages, Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional

Heteroskedasticity (GARCH).[48,85] However, all those assume linear models for prices and detecting non-linear relationships may improve prediction accuracy, as stated by Kumar and Thenmozhi (2014, p. 287).[66] Those authors argue non-linear models outperform traditional linear statistical techniques, generating more accurate predictions. Empirical results in previous studies points out to better performance obtained by non-linear models.[110]

Machine Learning algorithms are able to capture non-linear relationships in prices and have been widely used in financial prediction.[23] Those algorithms are a collection of specialized techniques for classification and regression, solving real life problems, including future movement of stock prices.[48] Machine Learning involves pattern recognition based on previous training from historical data. Most of the techniques have been applied with some success in previous studies, for example, k-Nearest Neighbors (kNN) in Zhang et al.[110], Artificial Neural Network (ANN) in Zhong and Enke [112] and Support Vector Machine (SVM) in Pan et al.[83]

Computer technology is being applied in the financial area, enabling analysis of big sets of historical data for decision support systems[29]; p. 195). Of those computerized machine learning techniques, ANN and SVM are extensively used in forecasting market prices.[52,84] Although comparisons and methods vary in each study, some authors claim best results for each algorithm. As examples, Patel et al. (2015a, p. 268)[54] show that ANN performs slightly less than SVM and other models, while Dash and Dash (2016, p. 56)[38] obtain more profits from the use of an ANN variation over SVM. Authors agree, however, that both models are capable of capturing non-linearities of stock prices.

In this study, we apply Moving Average Rules and Machine Learning algorithms to predict the price of Bitcoins. The results of our study should be of interest, mainly, to practitioners and policy makers. Active traders and market timers, with high risk tolerance, are continuously searching for strategies aiming to generate abnormal profits.

Additionally, we choose to compare Bitcoin with precious metals like gold and silver because they play a central role to those who do not trust fiat currencies that are related to central banks and governments. Such investors run into gold and silver whenever they feel that they lost trust in central authority. Bitcoin is viewed by some as an alternative to precious metals in this since as investors flee to it in times of crisis. Bitcoins are similar to gold in that they are both being traded globally 24 h daily. Also, they are both mined and not backed by a government with decentralized process. Damodaran[37] argues that Bitcoin is closer to being a currency with limited usage as a medium of exchange. He also argues that Bitcoin are neither an asset nor a commodity since it does not generate cash flows and that it cannot be used as raw material to produce something beneficial. Dyhrberg[43] argues that Bitcoins are something in between a currency and a commodity.

The main results of our paper can be summarized as follows. Compared to other precious metals traded in the currency market, Gold and Silver, Bitcoin presented an extremely better profitability for almost every strategy and, surprisingly a better performance in a risk-adjusted base.

This paper is structured as follows. In Sec. 2, we presented a literature review about the Bitcoin origins, its fundamentals and its spread around the world, as well the notion of market efficiency and a brief introduction to Artificial Intelligence. Sec. 3 addresses the data used and the chosen research methods. In Sec. 4, we present the main outputs of our algorithm and discuss conclusions that can be drawn from results. Sec. 5, presents some limitations and suggestions for further studies, emphasizing the relevance of the study.

2. Literature review

2.1. A general outline of Bitcoin

In the past few years, fiat money, as a currency which drives its value from a confidence relation within an economy, faced some challenges, due to a distrust on banks and traditional currency after the 2008 crisis,[19] leaving room for the emergence of digital currencies. Being synthetic, not tangible and not created by a nation, digital currency is not adopted officially by countries and it is protected by virtual anonymity.[8]

As a subset of digital currencies, cryptocurrencies, which denomination derives from the use of digital cryptographic algorithms, allow online payments without a third party to validate the transactions, as these are done by a cryptographic proof-of-work.[31]

According to Nian and Chuen (2015, p. 9)[80], the first cryptocurrency, eCash, was established in 1990, derived from Chaum.[25] eCash provided on-line and off-line payments, following cryptographic protocols and using blind signatures, which prevented double-spending and protected privacy of users.[80] Among hundreds of cryptocurrencies (up to 600),[8] Bitcoin is the most known and used. According to Dwyer (2015, p. 82),[42] the beginning of Bitcoin refers to a paper from an individual or a group under the pseudonym of Satoshi Nakamoto in 2008, which introduced a new currency with a specific production instructions. BTC has an open protocol and the currency is not owned by a single entity.[42] The open protocol permits changes that can become definite if is accepted by the majority of users.[31]

Bitcoin started in January 2009[20] and constitutes a digital currency that eliminates the need for a third party to validate the execution of payments.[88] Bitcoin is not traded in physical format and is not issued by a central authority.[87] In 2016, its traded volume may have reached $92 billion Bitcoins.[69]

As briefly presented earlier, Bitcoin has a limited amount of currency and, by 2040, one expect a quantity close to 21 million coins.[31] This limitation leads to two challenges: potential deflation and problems in double-spending. According to the author, when Bitcoin was first created, the main goal was to establish a decentralized management mechanism to avert the need for trusted third-parties. The design of Bitcoin can lead, on a long term, to a reduction in its price due to a decrease in its usage.

Given the existence of a known maximum number of coins, individuals would expect that the creation of new Bitcoins will eventually end. Increasing spending with Bitcoins will make them more valuable in the short term. However, individuals may be reluctant in selling the currency, expecting an increase in price. This rationale may decrease the supply of coins and, in the long term, slow down the Bitcoin economy, leading to a lower acceptance and to plummeting prices.[50]

Regarding safety, the decentralization of the Bitcoin system prevents attacks.[19] However, a fraud can occur with the modification and validation of several ledgers,[8] which must be done in a short amount of time, requiring a massive computer power. Bradbury (2013, p. 6)[19] states that since transactions with Bitcoins are not reversible, attackers can double-spend by gaining control of 51% of the hash rate.

Halaburda and Sarvary[50] analyzed online cryptocurrency exchanges and identified an increase in the price of Bitcoin as the use of the network raised, questioning whether it was being actually used as a currency or for trading purposes. In fact, Blau (2017, p. 493)[13] specifically studies the prices dynamics and speculative trading of the Bitcoin market. As Selgin[92] suggests, Bitcoin can considered a speculative commodity and therefore one can try to apply Technical Analysis (TA) strategies to trade this digital currency.

A number of studies investigate the diversification benefits of adding Bitcoins to the portfolios of investors. For example, Wu and Pandey[106] document evidence that Bitcoins enhance the efficiency of the portfolio when added to other asset classes. This is consistent with Brière et al.[21] who show that Bitcoins provide diversification benefits. Similarly, Carrick[22] shows that Bitcoins complement a portfolio of emerging market currencies by improving risk-adjusted returns. Recently, Bouri et al.[17] reconfirm that Bitcoins are suitable for diversification. Also, some studies show that Bitcoins provide hedging benefits for investors.[44] However, this is in contrast with findings of Bouri et al.[17] who demonstrate that Bitcoins are a poor hedge generally. Diversification and hedging benefits are time-varying and differ between different markets.[18]

However, a number of researchers point to the fact that Bitcoins carry higher risks and volatility which could make them less attractive to risk-averse investors.[21,42,58,103] To demonstrate such risks, an investor must be aware that the price of Bitcoins dropped by as much as 45% in a single day (i.e. April 11th, 2013). The Securities and Exchange Commission (SEC) lists several potential risks which are associated with Bitcoins such as the fact that Bitcoins are not insured. Also, government regulations could restrict usage of Bitcoins. In addition, there are security concerns raised by SEC on Bitcoins such as fraud, technical glitches and risk hackers.

A strand of the nascent digital currencies literature examines bubbles in Bitcoins and the extent of it being a speculative instrument.[26,28,34] For instance, Cheah and Fry[26] argue that Bitcoins have zero fundamental value and demonstrate that Bitcoins are prone to speculative bubbles. Similarly, Cheung et al.[28] detect several short-lived and at least three long speculative bubbles in Bitcoins. Borrowing econophysics models, Fry and Cheah[46] investigate bubbles and crashes in Bitcoins. They document a negative bubble resulting in dramatic price decline in Bitcoins from January 2014 to February 2015.

Bitcoins lack any intrinsic value and depend on the trust of market participants in the peer-to-peer network, open-source algorithm and demand which is driven by transparency and limited supply. Studying the financial economics of Bitcoins, Ciaian et al.[32] show that Bitcoins prices are affected by demand and supply market forces (e.g. size of Bitcoin economy, number of transactions) and Bitcoin attractiveness (i.e. online information queries regarding Bitcoins). Global macroeconomic factors have a short-term effect on Bitcoin prices[32]. Dwyer[42] provides an overview of the demand and supply regarding Bitcoins and argues that Bitcoins have a positive value in equilibrium.

The Nobel Laureate Eugene Fama developed the Efficient Market Hypothesis (EMH).[45] The notion of market informational efficiency states that market prices reflect information (i.e. historical public information cannot be used to better predict future movements in prices). Thus, investors cannot consistently beat the market in risk-adjusted basis in an efficient market. Several empirical studies tested the EMH in different asset classes with mixed results. For a detailed and comprehensive literature review on the efficient market hypothesis, the reader can refer to Ang et al.[3]; Degutis and Novickyte[39]; Lim and Brooks[70]; Ţiţan[99]; Yen and Lee.[107]

Lo[71] extends the EMH to better explain the time-varying nature of efficiency found in several asset classes. Lo[71] proposes the Adaptive Market Hypothesis (AMH) which assumes that humans make mistakes which could cause arbitrage opportunities to exist during certain time periods. Such opportunities disappear once exploited. Thus, under AMH, investment strategies do not always work and managers need to be consistently examining the effectiveness of applying alternative investment strategies. A number of studies examined the AMH in stock markets Kim et al.[60]; Urquhart et al.[104]; precious metals Charles et al.[24]; Urquhart[101] and currencies Neely[79]; Cialenco and Protopapadakis[33]

Few studies examine the informational efficiency of Bitcoins.[6,9,67,75,101] Examining calendar anomalies in Bitcoins, Kurihara and Fukushima[67] document significant day-of-the-week effect in Bitcoins. Such evidence is against the weak-form of the Efficient Market Hypothesis (EMH). However, they expect Bitcoins to be more informationally efficient with the increase in number of transactions and volume traded. Recently, Almudhaf[2] documents significant pricing inefficiency in Bitcoin investment trust.

While most studies examined the weak-form efficiency, Bartos[9] investigates the semi-strong form of market efficiency by testing the reaction of Bitcoins to public events. Bartos[9] finds that Bitcoins reflect public information and react to news which indicates that Bitcoins are semi-strong efficient. Extending this strand of the literature on predictability to a different dimension, Balcilar et al.[6] use nonlinear econometric methods to show that there is a significant relationship between volume and returns of Bitcoins. They also document several structural breaks in the data of Bitcoins. Thus, they suggest that traders can benefit from volume to construct strategies enhancing their profits. Such evidence points towards inefficiency of Bitcoins in its weak-form. Prior findings indicate informational inefficiency in Bitcoins which motivates us to dig further on whether we can take advantage of this predictability and generate abnormal profits using some simple trading rules.

2.2. A brief introduction to artificial intelligence

After the World War II, which fostered relevant technological advances, the use of machines spread in different industries and the discussion of intelligent machines started to become common. Alan Turing, an English mathematician, is one of the first researchers to address the question of artificial intelligence. Although Artificial Intelligence evolved from computer science,[86] it is not part of a single field any more, having links to various disciplines such as philosophy, mathematics, economics, finance, business administration, computer engineering, medicine, neuro science, etc … Although being studied for a long time, the general concept of “Intelligence” is hard to characterize and even before Christ, Aristotle already had thought and developed laws for the rational part of the mind.[90]

Human intelligence is a complex construct and machine intelligence is even harder to understand. For Russell and Norvig,[90] artificial intelligence is related to systems that are capable of think and learn, encompassing a broad set of tools, algorithms and techniques.[56] Some researchers, such as Russell and Norvig,[40] cast doubt on the possibility of machines to learn and think, despite becoming a real competitor in activities currently performed by humans and showing evidence of intelligence[72] or smartness in some specific contexts.

Regardless of the debate on machines depicting human learning and thinking, artificial intelligence has gained rapid momentum and large visibility in recent years.[56] AI is incorporated in our daily routine[63] and, in some situations, even overcoming performance of human beings. For instance,McCarthy[73] mentions applications in speech recognition and game playing. In this context, automated machines can adequately and effectively answer questions from humans through computers and cellphones using principles of AI. Machines can also play high level chess and go, an eastern board game, analysing a huge number of potential combinations of moves, defeating human world champions.

Machine Learning techniques, as a subset of IA, are widely used in financial data prediction, specially ANN and SVM. As a pioneering study on forecasting market index prices, McCarthy[61] suggests that previous studies show some limitations on the ANN pattern learning capabilities because of complexity of market dimensionality.[61] ANN works by minimizing empirical risk while SVM minimizes structural risk. Therefore, while ANN focuses on classification error reduction, SVM seeks the minimum upper limit for the generalization error.[61] Experimentally, the author shows SVM outperforms ANN, using Technical Analysis (TA) indicators as inputs.

Opposing results are found in the work of McCarthy[57], who also use ANN and SVM in market index direction forecasting. They use 10 years of daily historical data of the Istanbul Stock Exchange index, deriving TA indicators used as inputs for the prediction models. Although both models show impressive performance, ANN resulted in more accuracy on daily direction prediction in the testing data. A very similar work is done by Patel et al.[84], who also include more models in their comparisons.

As Machine Learning techniques are developed, it is common practice to assess their capabilities in financial data prediction,[52] due to the inherent challenges mentioned before. Therefore, authors bring comparisons among various methods, as done by Patel et al.[48] and Hsu et al.[52] Accuracies vary in each study, and Hsu et al.[52] particularly concludes they do not constitute strong enough evidence to contradict the EMH. They report accuracies below 60%.[52]

However, stock market prediction literature is rich in techniques comparisons. Son et al.[94], for example, bring another Machine Learning classifiers comparison on market index prediction. The authors also use TA indicators as input variables, but they perform dimensionality reduction through Principal Components Analysis (PCA), which measures each variable importance for the classification. For the SVM specifically, there is no significant improvement in applying PCA to the inputs before data classification.[94] Variable selection is also considered by Żbikowski,[109] who uses SVM in stock prices prediction using TA as input data.

Variable selection can improve the speed of execution and reduce the computational costs of Machine Learning algorithms.[65] In this context, Żbikowski[65] study accuracy prediction of a modified SVM with faster execution and variable selection capabilities. The algorithm is used in the next day direction forecasting. Also seeking directional predicting, Novak and Veluščček[81] study achieves 53.54%−64.11% hit rate using SVM classifier and TA input data, without any variable selection method. Novak and Veluščček[81] propose using classification results in trading strategies, evaluated by compound annual growth rate. Their results indicate strategies based on SVM are better choices than a buy-and-hold benchmark of the S&P500.

More recently, some studies hybridize classification techniques in order to overcome individual weakness and improve overall accuracy. Kumar and Thenmozhi[66] argue that financial time series are not absolutely linear or non-linear and propose the use of a hybrid form of the Forests (RF). Patel et al.[85] applies a special SVM used for two types of models. The authors then combine ARIMA with SVM, ANN and Random regressions in TA data before classification by a second algorithm, such as ANN. Finally, Nayak et al.[77] and Chen and Hao[27] propose hybridizing SVM and kNN classifiers, always using TA indicators as input variables. The work done by Chen and Hao[27] evolves the approach of Nayak et al.[77] by adding a weighting measure for each variable based on information gain.

3. Data and simulation

The data of this study were based on daily records on Bitcoin, Gold and Silver quotations, in dolar, including information about open, high, low and close prices, retrieved from Bloomberg®. The data from Bitcoin goes from 05/07/2012 to 05/04/2017, which totals 1,302 observations. Gold and Silver data's window are both from 04/16/2012 to 05/04/2017, which totals 1,272 observations. To analyse the trading performance and prediction power of the model, we only used the close data from either.

The main goal of this paper is to provide conclusions about the application of Machine Learning to historical prices of Bitcoin in comparison with Gold and Silver. To accomplish this objective, we developed a model to run the simulations with price data. The model consists of a trade system, whose inputs are essentially close prices and the output is a set with a large number of statistics evaluating the simulation performance for each strategy stated.

The Machine Learning techniques that we explore in this study is based on Support Vector Machines (SVM) and Artificial Neural Networks (ANN). SVM was introduced in the work of Nayak et al.[105], following a structural risk minimization principle.[61] Being one of the most used Machine Learning techniques for financial markets prediction, it maps input vectors $\mathbf{x}_k$ into a high-dimensional feature space, where a decision boundary is built from a linear model, as discussed by Nayak et al.[105] This work applies SVM to predict the next day market direction from Moving Averages used as input variables in order to develop buy and sell signals. Therefore, a market strategy is devised according to prior classification considering historical price data.

Specifically, consider $\{(\mathbf{x}_k, y_k)\}_{k=1}^{N}$ all the training observations already classified as $y_k \in \{-1, 1\}$. In the current case, the $\mathbf{x}_k$ vectors consist of Moving Average values, using both SMA and EMA calculated using 2, 15, 20 and 60 periods. Therefore each observation, which translates to a trading day, has eight input variables to the SVM model. All training observations are already qualified as up or down in prices relative to their previous day. Those directions are labels, encoded as $y_k \in \{-1, 1\}$, in which 1 relates to price increase and -1 to price decrease.

Input vectors of m dimensions are mapped to a high-dimensional feature space by a $\phi(\cdot) : \mathbb{R}^m \rightarrow \mathbb{R}^{m_z}$ transformation, where they have m_z dimensions. In this new space, the algorithm attempts to fit a linear classification model, building a separating hyperplane $\mathbf{w}^T \phi(\mathbf{x}) + b = 0$, where $\mathbf{w}$ is a weights vector and b is a constant scalar.[54,66,94] Observations are then classified according to Eq. (1) and Eq. (2), which are summarized as $y_k[\mathbf{w}^T \phi(\mathbf{x}_k) + b] \geq 1$.

$$\mathbf{w}^T \phi(\mathbf{x}_k) + b \geq 1 \text{ for } y_k = 1 \tag{1}$$

$$\mathbf{w}^T \phi(\mathbf{x}_k) + b \leq -1 \text{ for } y_k = -1 \tag{2}$$

Even in the high dimensional $\mathbb{R}^{m_z}$ space, it may be impossible to obtain a perfect classification mechanism taking into account $y_k[\mathbf{w}^T \phi(\mathbf{x}_k) + b] \geq 1$ hyperplane. To tackle this issue, Vapnik[105] introduces a non-negative parameter ξ as a tolerate classification error.[108] The hyperplane is then rewritten as Eq. (3) and the main objective of SVM is maximizing its margin $\|\mathbf{w}\|$.[109] The problem can be formulated as the minimization Eq. (4), where the parameter C is an upper bound limit for errors.

$$y_k[\mathbf{w}^T \phi(\mathbf{x}_k) + b] \geq 1 - \xi_k \tag{3}$$

$$\min \phi(\mathbf{w}, b, \xi) = \frac{1}{2}\mathbf{w}^T \mathbf{w} + C \sum_{k=1}^{N} \xi_k \tag{4}$$

Vapnik[105] suggests solving Eq. (4) by using Lagrange multipliers, resulting in the classification decision function of Eq. (5). For the detailed mathematical deriving of that equation, please refer to Huang et al.[54], Pai and Lin[82] and Yu et al.[108] It remains to be specified the mapping function $\phi(\cdot) : \mathbb{R}^m \rightarrow \mathbb{R}^{m_z}$ in Eq. (5) for practical classifications using the model. A kernel function $K(\mathbf{t}, \mathbf{u}) = \phi(\mathbf{t})^T \phi(\mathbf{u})$ is considered for any dimensionality manipulation without explicit knowledge of $\phi(\cdot)$. Eq. (5) is then rewritten in the form of Eq. (6).

$$f(\mathbf{x}) = sgn\left[\sum_{k=1}^{N} \alpha_k y_k \phi(\mathbf{x}_k)^T \phi(\mathbf{x}) + \frac{1}{N_s} \sum_{0<\alpha_j<C} \left(y_j - \sum_{k=1}^{N} \alpha_k y_k \phi(\mathbf{x}_k)^T \phi(\mathbf{x}_j)\right)\right] \tag{5}$$

$$f(\mathbf{x}) = sgn\left[\sum_{k=1}^{N} \alpha_k y_k K(\mathbf{x}_k, \mathbf{x}) + \frac{1}{N_s} \sum_{0<\alpha_j<C} \left(y_j - \sum_{k=1}^{N} \alpha_k y_k K(\mathbf{x}_k, \mathbf{x}_j)\right)\right] \tag{6}$$

The $K(\mathbf{t}, \mathbf{u})$ function selected for the present work, which satisfies mathematical conditions exposed by Vapnik[105]; is the radial function of Eq. (7). It is a popular choice for kernel function, as used by Ballings et al. (2015, p. 7049)[7], Novak and Velušček (2016, p. 795)[81], Hsu et al. (2016, p. 222)[52] and Pan et al. (2017, p. 93)[83]. It should be noted that in Eq. (7) the γ radius is a parameter for optimization. Along with C described before, γ is selected as the best performing value in parametrization procedure.

$$K(\mathbf{t}, \mathbf{u}) = e^{-\gamma\|\mathbf{t}-\mathbf{u}\|^2} \tag{7}$$

Concerning Artificial Neural Networks (ANN), one of the first machine learning techniques, are computational tools that tries to learn from inputs and outputs, aiming to detect patterns and predict future realizations of random variables, based on an inductive method.

According to Haykin,[51] ANN are develop to behave like the human brain, with information being processed by neurons that interact among themselves.[78] In Artificial Neural Networks, the interaction among neurons lead to weights that represent the way each neuron assess relevance of inputs, in order to generate outputs.[4] Similarly to the way biological neurons changes their own structure to perform cognitive tasks, artificial neurons change their parameters, or weights, to execute distinct computational works.

Furthermore, Angelini et al.[4] summarizes the general behaviour of a single neuron in a ANN. First, the weighted sum of the neuron input data is evaluated and this value is used as a new input for some activation function. It is worth noting ANN is a general class of predictive models, once the most simple ANN model is a linear regression in which the activation function is no other than the identity function.

According to the usual notation on Artificial Neural Network we can say the above example has one input layer, which refer to the raw data as input and one hidden layer, concerning the new input generated from the weighted sum of input. The hidden layer is provided by a single neuron, the one which generated the weighted suns.

Artificial Neural Networks have been constantly used in Finance, both in practical sense and in the theoretic framework. In the latter case, many studies feasibility of the use of Artificial Neural Networks in order to predict prices of currencies (Czekalski et al.[36], Huang et al.[53], Nasution and Agah [76] and Tenti[96]) and stocks Guresen et al.[49], Moghaddam et al.[74] and Zhang and Wu[111]. Angelini et al.[4], on the other hand, analyse the power of Artificial Neural Network when it comes to create a solid credit score system. To the best of our knowledge, we are the first to apply a ANN algorithm in order to attempt to detect short run behaviour of Bitcoin prices. In this sense, Ticknor[98] says ANN are better suitable for small-range data.

Opposing to SVM, ANN classifiers consist of interconnected layers in a network which mimics human nervous system.[112] Each layer, with varying number of neurons, is connected to the next until a single output is calculated, given a number of input variables. The interconnections are weighted by values optimized during the training phase, in the same fashion as SVM, determining the best parameters for a given pre-classified training data set. This article follows Patel et al.[85] in using three layer Artificial Neural Networks and applying an adaptive gradient descent for updating the interconnection weights.

The 60 days used for optimization are further divided into three groups. The first 15 trading days are used for parameter selection training data. The second group, consisting of the next 15 days, are used for parameter testing data. After parameter selection, the model fits the next 30 days, classifying market direction for the next trading day as up or down. Parameter selection is done by the most accurate combination of values, with accuracy defined as Patel et al. (2015a, p. 265)[84] in Eq. (8), where *TP* are the True Positives, *TN* the True Negatives, *FN* the False Negatives, and *FP* the False Positives.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{8}$$

For selection of parameters in the training data, the first 15-day group is used for fitting SVM models of varying parameters. As done by Kara et al.[57] and Patel et al.[84], a grid search is conducted for values $C \in \{0.5, 1.5, 10, 100\}$ and $\gamma \in \{0.5, 1, 1.5, 2, \ldots, 10\}$. Models considering all possible combination of those values are evaluated over the parameter testing data, the second 15-day group. The C and γ values which result in the most accurate model, according to Eq. (8), are selected for the final model training. That last step is done using the last 30 trading days to produce a forecast for the next day. As for ANN parameters, we set 10 as the number of neurons in the hidden layer, 0.1 as the learning rate and momentum constant. Weights are optimized daily. To compare the profitability and risk performance of each currency at the portfolio four indicators were evaluated. They are:

- Profit factor: Let the gross profits earned from the trading of the asset i, based on available data, be GP_i and let the corresponding gross losses be denoted by GL_i. The profit factor of that asset, PF_i, is defined as follows:

$$PF_i = \frac{GP_i}{GL_i} \tag{9}$$

- Average Win *vs* Loss ratio: Let w_i be the number of transactions which ended in profit and l_i be the number of transactions which ended in loss. The average win *vs* loss ratio of the currency i, denoted by AR_i, is defined as:

$$AR_i = \frac{GP_i/w_i}{GP_i/l_i} \tag{10}$$

- Profit to maximum drawdown: Let D_i be the maximum drawdown of the currency i, which represents the maximum difference between successive peaks and valleys in the trade performance of that asset. Moreover, let R_i be the return of the asset i, which represents the final amount obtained. The profit to maximum drawdown, PD_i is defined as follows:

$$PD_i = \frac{R_i}{D_i} \tag{11}$$

- Annualized Sharpe ratio: Let AD_i be the average daily profit *vs* loss of the currency i, daily mean of realized profit and loss on days there were transactions, and σ_i be its standard deviation. The annualized Sharpe ratio, SR_i is defined as:

$$SR_i = \frac{AD_i}{\sigma_i} \times \sqrt{252} \tag{12}$$

These kind of metric based on Sharpe ratios and drawdown are frequently used to evaluate performance of strategies as has been seen in Lee et al.[68] Teplova et al.[97] and Bohl et al.[14]

4. Results

We compare results of the Machine Learning techniques applied to prices of Bitcoins, Gold and Silver. This comparison follows other studies that confront Bitcoin and currencies and commodities, specially Gold (e.g.Dyhrberg[44], Dyhrberg[43], Baur et al.[12], Sensoy[93], Gajardo et al.[47], Bouri et al.[16]), aiming to analyse behaviour, comovements and opportunities of diversification and hedging with this cryptocurrency. Additionally, due to their characteristics as precious metals, Gold and Silver have their relationship frequently studied such as in Batten et al.[10], Schweikert[91] and Dutta[41] that, respectively, analyse potential price manipulation, assess cointegration and investigate volatility spillovers of these two assets. Therefore, the study of Bitcoins, Gold and Silver can indicate trading opportunities as well as hedging possibilities.

Machine Learning techniques could be useful to explore short-term fluctuations by recognizing patterns on price behaviour, regardless of the medium and long-term up trends in the value of Bitcoins. We enhanced our analysis, using Artificial Neural Networks and comparing results with a buy-and-hold strategy, aiming to highlight the capability of machine learning techniques in capturing short-term trends and leading to relevant risk-adjusted returns. Due to its nature, machine learning can identify patterns from complex and non-linear behaviour.

Two really interesting findings were obtained comparing all the tables: (i) All the samples indicate that SVM provided better returns than buy-and-hold for Gold and Silver. However, ANN showed poor performance for both of them on almost all the samples; (ii) Where the ANN was able to surpass Gold and Silver (the sub sample between May 2015 and April 2017), it was able to surpass even Bitcoin returns and by an expressive amount.

During the period from May 2015 to April 2017 the cryptocurrency showed a strong bull tendency, as showed in Fig. 1. The average agent would believe buy and hold will surely beat any active and automated trading rule but this is not the case for this period, since the initial equity grows with a proportion around 13 (even accounting for extremely high fixed costs) using ANN and around 5 with the passive strategy.

During another sub period in which the ANN showed poor performance are presented in Fig. 2. Its worth noting that for both periods in Figs. 1 and 2, SVM performance did not change much, being beat by buy-and-hold for Bitcoin but showing better performance for Gold and Silver. Moreover, comparing performance of SVM and ANN in the forecasting strategy described before across the three commodities, it can be observed both classifiers have slightly better accuracy results for Bitcoin.

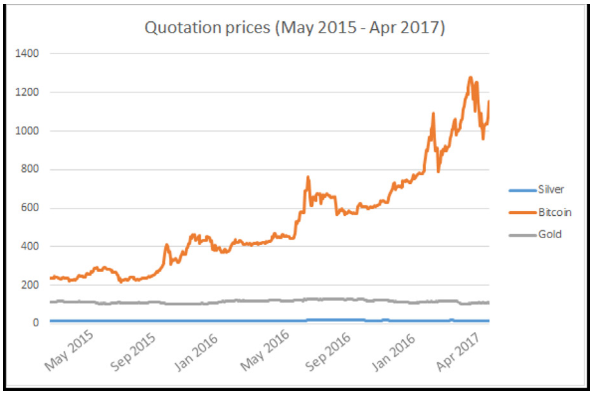

Fig. 1. Quotation prices for whole sample in dollar.

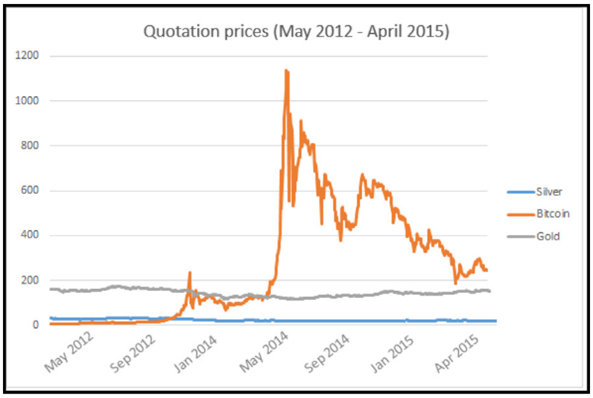

Fig. 2. Quotation prices from May 2012 to April 2015 in dollar.

We obtained, therefore, that SVM are better suitable for agents with risk aversion, once it produces better returns on the risk-adjusted basis than buy-and-hold for both traditional currencies like Gold and Silver and new instruments like Bitcoin. On the other hand, ANN has great potential to generate abnormal returns in short run periods but exposes the investor to more risk. Tables 1—13.

Table 1
Performance measures without transactions cost for SVM using the whole historical data prices.

	Bitcoin	Gold	Silver
Profit factor:	1.17988	0.76110	1.09982
Average Win/Loss:	1.76981	0.90227	1.32595
Profit to maximum drawdown:	3.73827	−0.38714	0.35035
Annualized Sharpe ratio:	−0.00917	−0.32757	−0.14784
Hit rate:	57.41%	49.87%	52.26%

Table 2
Performance measures without transactions cost for SVM using historical data prices from May 2012 to April 2015.

	Bitcoin	Gold	Silver
Profit factor:	1.1148	0.80451	1.40706
Average Win/Loss:	1.5065	0.93093	1.38724
Profit to maximum drawdown:	1.2112	−0.22867	0.75415
Annualized Sharpe ratio:	−0.01243	−0.34387	−0.15262
Hit rate:	57.32%	48.29%	52.31%

Table 3
Performance measures without transactions cost for SVM using historical data prices from May 2015 to April 2017.

	Bitcoin	Gold	Silver
Profit factor:	3.03386	1.21000	0.91996
Average Win/Loss:	3.15522	1.02666	1.21356
Profit to maximum drawdown:	4.16915	0.13202	−0.07710
Annualized Sharpe ratio:	−0.04769	−0.29778	−0.36326
Hit rate:	59.75%	50.39%	53.93%

Table 4
Performance measures with transactions cost of 5$ for SVM using the whole historical data prices.

	Bitcoin	Gold	Silver
Profit factor:	1.17884	0.68228	1.06815
Average Win/Loss:	1.79008	0.93146	1.29775
Profit to maximum drawdown:	3.70018	−0.50411	0.23226
Annualized Sharpe ratio:	−0.00924	−0.40356	−0.16144
Hit rate:	57.41%	49.87%	52.26%

Table 5
Performance measures with transactions cost of 5$ for SVM using historical data prices from May 2012 to April 2015.

	Bitcoin	Gold	Silver
Profit factor:	1.11384	0.74648	1.36300
Average Win/Loss:	1.53530	0.89794	1.38220
Profit to maximum drawdown:	1.21108	−0.29376	0.66379
Annualized Sharpe ratio:	−0.01250	−0.37694	−0.16083
Hit rate:	57.32%	48.29%	52.31%

Table 6
Performance measures with transactions cost of 5$ for SVM using historical data prices from May 2015 to April 2017.

	Bitcoin	Gold	Silver
Profit factor:	3.00516	1.09488	0.86264
Average Win/Loss:	3.24557	0.97697	1.15630
Profit to maximum drawdown:	4.37120	0.06103	−0.13322
Annualized Sharpe ratio:	−0.04793	−0.31799	−0.38653
Hit rate:	59.75%	50.39%	53.93%

Table 7
Performance measures without transactions cost for ANN using the whole historical data prices.

	Bitcoin	Gold	Silver
Profit factor:	1.79784	0.46154	0.31559
Average Win/Loss:	1.88774	0.58580	0.53256
Profit to maximum drawdown:	1.72567	−0.34746	−0.56469
Annualized Sharpe ratio:	−0.00549	−0.31069	−0.45184
Hit rate:	56.26%	48.39%	50.31%

Table 8
Performance measures without transactions cost for ANN using historical data prices from May 2012 to April 2015.

	Bitcoin	Gold	Silver
Profit factor:	1.29488	0.36648	0.27806
Average Win/Loss:	1.39448	0.69632	0.55611
Profit to maximum drawdown:	0.44941	−0.31486	−0.54622
Annualized Sharpe ratio:	−0.00527	−0.39044	−0.57450
Hit rate:	51.38%	47.51%	47.69%

Table 9
Performance measures without transactions cost for ANN using historical data prices from May 2015 to April 2017.

	Bitcoin	Gold	Silver
Profit factor:	13.25790	2.65723	1.35129
Average Win/Loss:	6.62895	1.77149	1.68911
Profit to maximum drawdown:	4.76316	0.15721	0.04747
Annualized Sharpe ratio:	−0.05645	−0.29130	−0.32027
Hit rate:	61.73%	51.69%	52.88%

Table 10
Performance measures with transactions cost of 5$ for ANN using the whole historical data prices.

	Bitcoin	Gold	Silver
Profit factor:	1.79590	0.42316	0.29512
Average Win/Loss:	1.97549	0.68074	0.51646
Profit to maximum drawdown:	1.72248	−0.37735	−0.58482
Annualized Sharpe ratio:	−0.00551	−0.32361	−0.47255
Hit rate:	56.26%	48.39%	50.31%

Table 11
Performance measures with transactions cost of 5$ for ANN using historical data prices from May 2012 to April 2015.

	Bitcoin	Gold	Silver
Profit factor:	1.29496	0.34859	0.26380
Average Win/Loss:	1.49418	0.69718	0.54790
Profit to maximum drawdown:	0.44940	−0.32757	−0.56205
Annualized Sharpe ratio:	−0.00529	−0.39751	−0.59309
Hit rate:	51.38%	47.51%	47.69%

Table 12
Performance measures with transactions cost of 5$ for ANN using historical data prices from May 2015 to April 2017.

	Bitcoin	Gold	Silver
Profit factor:	13.0973	2.50996	1.30395
Average Win/Loss:	7.48415	1.95219	1.95593
Profit to maximum drawdown:	4.74805	0.14829	0.04193
Annualized Sharpe ratio:	−0.05651	−0.29223	−0.32186
Hit rate:	61.73%	51.69%	52.88%

Table 13
Results per time period for buy-and-hold.

Period	Bitcoin	Gold	Silver
Whole sample.	314.48	0.73	0.50
May 2012–Apr 2015.	48.58	0.72	0.54
May 2015–Apr 2017.	4.91	1.055	1.11

5. Conclusion

Overall, our results indicate that the application of Artificial Intelligence techniques may be fruitful in both currency and cryptocurrency markets, depending on the method. Thus, such evidence casts doubt to the weak-form of efficiency in the Bitcoin market. This is consistent with prior findings of Urquhart[102]; who shows informational inefficiency in Bitcoins.

We complement the analysis of efficiency of Bitcoins considerating Support Vector Machine and Artificial Neural Network methods, since some studies like Urquhart[102] apply some econometrics techniques to analyse Bitcoin trading and obtain similar results. Our paper have an approach more close to the techniques frequently used for market practitioners.

Our contributions are twofold. First, we obtain that Support Vector Machine strategy should be used by investors willing to achieve more conservative returns on the risk-adjusted basis whether the investor choose traditional and consolidated instruments or choose the promising cryptocurrency market. Second, Artificial Neural Networks can really help the profitability of Bitcoin trading during short run bull trends, even accounting for transaction costs.

The latter result supports Adaptative Market Hypothesis, which states that arbitrage opportunities will exist from time to time. Moreover, low liquidity of Bitcoins, when compared to other conventional assets, could be a relevant factor for practical use the techniques in real-life situations, making it more difficult to exploit informational inefficiencies.

Our paper focuses on analysing machine learning techniques applied to the trading of Bitcoins. Taking into account the scope of the paper on the analysis of price behaviour, we do not try to make considerations about the conceptual features (e.g., whether Bitcoin displays characteristics of commodities or currencies) neither to discuss tax issues. Given the popularity of this cryptocurrency and its incipient theoretical and empirical framework, our study of Bitcoins can contribute to the analysis of trading opportunities that may emerge in the market. However, future research could explore regulation, taxation and currency or commodity characteristics and their implication in the pricing and trading of Bitcoins.

Future research can also extend our paper to include other cryptocurrencies (e.g. Ethereum, Ripple and Litecoin) and expand the number of trading rules applied to Bitcoins while adjusting for data-snooping bias. In addition, there are several unexplored areas in the emerging literature regarding Bitcoins. For example, what is the relationship between policy economic uncertainty and Bitcoins? Moreover, one can apply Artificial Intelligence to Bitcoins using high frequency intraday data.

Conflicts of interest

The authors declare no conflict of interest.

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