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APPLICATION OF ARTIFICIAL INTELLIGENCE TO BITCOIN COURSE MODELLING

Artificial neural networks are modern methods suitable for solving the problem of nonlinear dependency approximation, which is successfully applied in many fields. This paper compares the predictive capabilities of Back Propagation, Radial Basis Function, Extreme Learning Machine, and Long-Short Term Memory neural networks to determine which artificial intelligence algorithm is best for modeling the price of Bitcoin opening. The criterion for comparing network performance was the standard deviation, the mean absolute deviation, and the accuracy of predicting the direction of change of course. At the same time, in the study of time series, it is recommended to perform a comprehensive data analysis using appropriate networks, depending on the length of the series and the specificity of the database.

Key words: Artificial intelligence; back propagation; radial basis function; extreme learning machine; long-short term memory; bitcoin.

Introduction. Prediction of stock prices and exchange rates is one of the most important tasks of quantitative finance. Particular attention is being drawn to new financial instruments – cryptocurrencies. The theory of price forecasting is a major topic of discussion in finance. With the advent of behavioral finance, many economists believe that stock prices, albeit partially, can be predicted on the basis of historical price patterns, which provides the basis for developing fundamental and especially technical analysis as tools for forecasting prices.

Bitcoin is a kind of digital currency that uses encryption methods to control the generation of currency units and to verify the transfer of funds that operate independently of the central bank [1-3]. In [4] authors investigate the relationship between Bitcoin and conventional financial assets from a perspective on the connectedness of asset networks. The separation of positive and negative returns in the Bitcoin market shows the existence of an asymmetric pattern of the spillover effects between Bitcoin and conventional assets. Eom [5] focuses on the relation between bitcoin prices and trading volume. The findings imply that fundamental uncertainty generates more dispersion in heterogeneous beliefs among investors and leads to high trading and to speculative bubbles. In [6] authors explore the occurrence and timing of bubbles in the Bitcoin USD rates. Being a very new and innovative currency, Bitcoin exhibits unique features that makes it different from other currencies. Musiałkowska et al. [7] aimed to find, which of the assets: gold, oil or bitcoin can be considered a safe-haven for investors in a crisis-driven Venezuela. The authors look also at the governmental change of approach towards the use and mining of cryptocurrencies being one of the assets and potential applications of bitcoin as (quasi) money. In [8] authors examine the resilience of Bitcoin (BTC) to hedge Chinese aggregate and sectoral equity markets and the returns spillover to Altcoins onset the Novel Coronavirus outbreak. Overall, gold outperforms BTC in hedging and safe haven perspectives with respect to Chinese equity markets.

Artificial intelligence models, especially neural networks, have already found numerous applications in quantitative finance, for example, to predict volatility. Within the paradigm of training with a teacher, neural networks are a useful tool for predicting prices, since they do not require initial assumptions that differentiate them from traditional time series forecasting models, such as ARIMA and its modifications.

Deep learning is coming to play a key role in providing big data predictive analytics solutions and data fragments are becoming larger. In [9], authors provide a brief overview of deep learning, and highlight current research efforts and the challenges to big data, as well as the future trends.

One of main advantages of deep learning is the ability to extract features from a large set of raw data without relying on prior knowledge of predictors. This makes deep learning particularly suitable for stock market prediction. In [10] the model was tested on high-frequency data from the Korean stock market.

In [11] authors demonstrated that deep learning is useful for event-driven stock price movement prediction by proposing a novel neural tensor network for learning event embeddings, and using a deep convolutional neural network to model the combined influence of long-term events and short-term events on stock price movements.

The type applications of Extreme Learning Machine (ELM) include classification and regression problems. In these problems, ELM has lower computational time, better performance, and generalization ability than the conventional classifiers, such as Back Propagation neural networks. In addition, ELM was also successfully applied on pattern recognition, forecasting and diagnosis, image processing, and other areas [12].

In recent years, deep artificial neural networks (including recurrent ones) have won numerous competitions in pattern recognition and machine learning. The historical survey [13] compactly summarizes relevant works, much of which were in the previous millennium. Shallow and Deep Learners differ in the depth of their ways of assigning credits that may be learning, of causation between actions and consequences.

Many modern scientific works are devoted to the research of the efficiency of using artificial neural networks. Adebiyi et al. [14] compared the predictive power of the ARIMA model and artificial neural networks in the context of Dell stock index modeling. Although the authors emphasize that both approaches are acceptable and sufficiently accurate for analysis, they nevertheless note that the artificial neural network model has shown better results. The results of similar studies are also presented in [15]. In [16] authors use support vector machine (SVM) learning algorithm to find whether it can predict Bitcoin prices and finds that SVM predicts five steps ahead Bitcoin prices for the short term, medium term, long term, and overall Bitcoin price level.

Chen et al. [17] examined which of the artificial intelligence algorithms best demonstrates itself when modeling the stock price index in the Chinese stock market. The authors investigated the predictive power of algorithms on time series of different lengths. The research concluded that it is advisable to use deep neural networks in predicting large data samples. Liashenko and Kravets [18] made a comparison of the predictive capabilities of Long Short Term Memory and Wavelet based Back Propagation neural networks for co-movement of time series for oil and gas prices, Dow Jones and US dollar indexes.

In [19], authors study the use of Support Vector Machines (SVM) to predict financial movement direction. SVM is a promising type of tool for financial forecasting. As demonstrated in empirical analysis, SVM is superior to the other individual classification methods in forecasting weekly movement direction of NIKKEI 225 Index.

This paper compares the predictive capabilities of different types of neural networks to determine the best artificial intelligence algorithm to model the price of Bitcoin opening.

Methodology.

Back Propagation Neural Networks (BP)

Back Propagation network is by far one of the most used and most popular models. The basic idea behind the BP algorithm is to divide the learning process into two steps: direct signal propagation and reverse error propagation. At the stage of direct signal propagation, input information is supplied from the input layer to the output layer through a hidden layer. Network weights are fixed during the direct signal transmission. At the reverse propagation step, an error signal that did not meet the precision requirement is propagated step by step, and the error is divided into all neurons of each layer. The link weights are dynamically adjusted according to the error signal [20]. The most common algorithm for finding weights that minimize error is the gradient descent method. The Back Propagation method is used to find the steepest descent direction [21].

Back propagation is probably the most well-studied neural network learning algorithm and is a starting point for most people looking for a network-based solution. One of its drawbacks is that it often takes many hours to prepare for problems in the real world, and therefore many efforts have been made to improve the training time [22].

Radial Basis Function Neural Networks (RBF)

RBF networks are three-layer artificial neural networks, each hidden layer neuron using a radial basis function as an activation function [17, 23]. The radial basis function is a function of real variables whose value depends on the distance to the origin of the coordinate system. The simplest training algorithm for this network involves using the gradient descent method. The criterion for optimizing the model is to minimize the root mean square deviation. You can also use clustering methods to determine the initial centers and the least squares method to find the initial weights [24].

Extreme Learning Machine (ELM)

ELM, as a relatively new algorithm for training three-layer neural networks, is very fast and efficient. Weights are calculated using mathematical transformations, which eliminates long learning processes with adjusting network parameters using iterative methods [12, 25].

The essence of ELM is that the learning parameters of hidden nodes, including input weights and biases, are randomly assigned and need not be tuned while the output weights can be analytically determined by the simple generalized inverse operation. The only parameter to determine is the number of hidden nodes. Compared with other traditional learning algorithms, ELM provides extremely faster learning speed, better generalization performance and with least human intervention [12].

Long-Short Term Memory Neural Networks (LSTM)

The LSTM networks are a special type of recurrent neural networks (RNN) that can study long-term dependencies. All RNN have the form of a chain of repetitive neural network modules. In a standard RNN, this repeating module has a simple structure of one layer. LSTM also has such a chain structure, but the repeating module has four layers [18, 26, 27].

The LSTM module (or cell) has 5 main components, which allows you to model both long-term and short-term data:

- the state of the cell is the internal memory of the cell, which stores both short-term memory and long-term memory;
- hidden state – this is the initial status information calculated for the current logon;
- input gateway – determines how much information from the current incoming stream enters the cell's state;
- "forget gate" – determines how much information from the current input and the previous state of the cell goes to the current state of the cell;
- output gateway – decides how much information from the current state goes into a hidden state.

Results. The future of bitcoin is very unpredictable. There are many possible options for its further development. There is an opinion that bitcoin has the potential to become a world currency. To do this, it must perform the functions of a medium of exchange, unit of account, and accumulation of value. The first of them cryptocurrency partially executes. Bitcoin is a means of accumulation in the sense that it can be sold and stored for future use. The tricky part is achieving a steady value for cryptocurrency, as its price is based mainly on the supply and demand relationship. At the same time, the price of bitcoin is very volatile.

Bitcoin has the potential to become an adjunct to the global financial sector as one way to transact with other global currencies. It is a widespread, decentralized database, designed to reach consistent and reliable agreement on transactions between independent network members [28].

If bitcoin can to some extent become a more controlled and stable currency, this way of transferring money globally has a great prospect, since it does not require the involvement of intermediaries. Other positive features of this cryptocurrency include its global availability, the ability to create multifunctional accounts, and the simplification of crowdfunding.

The highest cryptocurrency value at market is considered hedge against inflation because its supply is limited and its monetary policy is pre-programmed to reduce its rate of expansion by 50 percent every four years.

The day of halving the rewards of miners for the extraction of new coins is called the day of halving. The halving procedure reduces the number of new bitcoins that are paid for the completion of each new block on the blockchain. This means that the supply of new bitcoins will decrease. In traditional financial markets, lower supply at a steady demand tends to lead to higher prices. As halving also reduces the number of new bitcoins and the demand remains constant, this procedure also leads to an increase in the price of bitcoins. Bitcoin has historically come up with new price highs just before or after the next halving. Every halving lowers bitcoin inflation.

But a periodic decline in the bitcoin chasing rate can be more profound than any short-term price changes for the currency to function. Reward block is an important component of Bitcoin that ensures the security of this leaderless system. As remuneration drops to zero over the coming decades, it could potentially destabilize the economic incentives underlying bitcoin security.

A unique aspect of Bitcoin is that the programmed block reward decreases over time. This is different from the norm for modern financial systems where central banks control the money supply. Unlike the twice-reduced bitcoin premium, the dollar supply has increased about three-fold since 2000.

In order to simulate the bitcoin exchange rate, we used high-frequency Gemini cryptocurrency data. A database of every-minute bitcoin exchange rates for the period from January 01, 2020 to March 31, 2020 was downloaded for research. Fig. 1 shows the minute change of the Bitcoin exchange rate during March 01, 2020 to March 08, 2020. It is worth noting that the graph shows significant fluctuations in the course during this period. This allows us to draw some conclusions about the suitability of neural networks for prediction in the case of high accuracy of the obtained prediction.

Using neural network learning algorithms, it is necessary to prepare the data, which involves reducing the difference between the threshold and the actual data. Typically, data is normalized before using it on a neural network. After calculations, an operation back to normalization is performed.

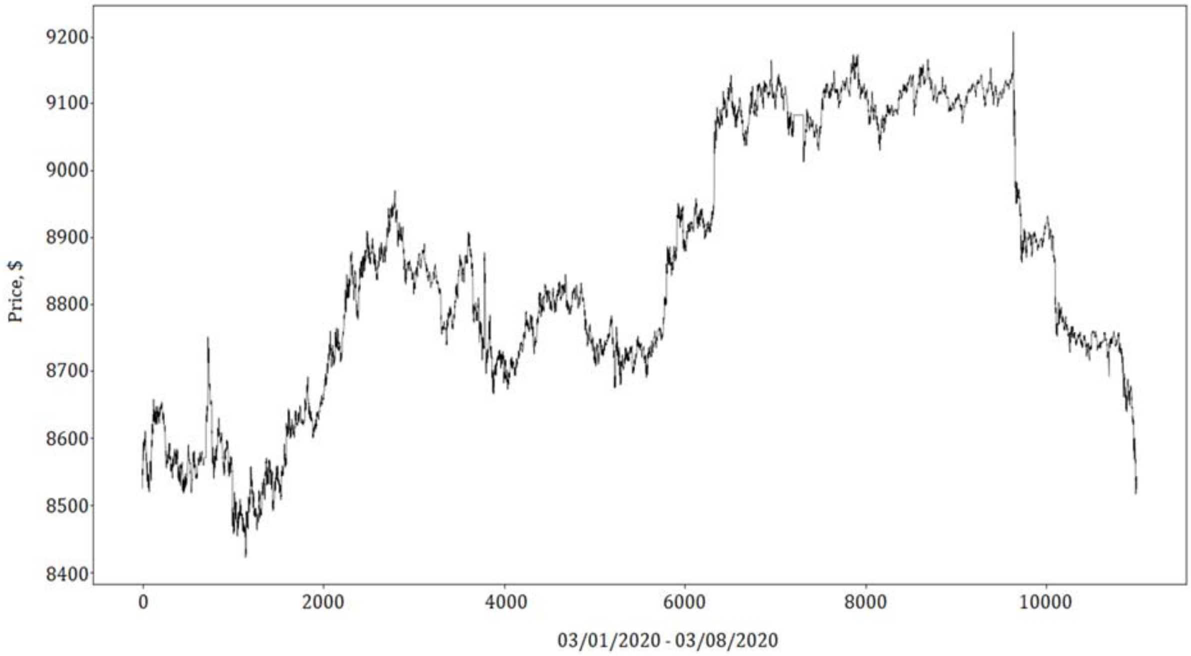

Fig. 1. Every-minute Bitcoin course

Source: www.cryptodatadownload.com/data/gemini/

Three criteria are used to estimate the forecasting accuracy of a study: root mean squared error (RMSE), mean absolute percentage error (MAPE), and directional accuracy (DA) [28].

RMSE characterizes the standard deviation between the predicted and actual values:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\hat{y}_t - y_t)},$$

where y_t and $\hat{y}_t$ – the actual and predicted price according to time *t*, N – the length of the test dataset.

MAPE estimates the accuracy of the forecast in percentage terms and is defined as

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{\hat{y}_t - y_t}{y_t}\right|.$$

RMSE and MAPE are used to measure prediction accuracy. The smaller they are, the higher the accuracy of the model.

The accuracy of predicting the direction of change of course is defined as

$$DA = \frac{1}{N}\sum_{t=1}^{N} D_t, \quad D_t = \begin{cases} 1, \ (y_{t+1} - y_t)(\hat{y}_{t+1} - y_t) \geq 0, \\ 0, \ (y_{t+1} - y_t)(\hat{y}_{t+1} - y_t) < 0. \end{cases}$$

The closer DA is to one, the higher the accuracy of forecasting the direction of price change.

During the study, the database was initially divided into 5 consecutive sets of 2200 values (small datasets). These sets contain data on Bitcoin open price for the periods from March 01, 2020 (00:00 a.m.) to March 02, 2020 (00:39 p.m.), from March 02, 2020 (09:19 a.m.) to March 03, 2020 (09:59 p.m.), from March 03, 2020 (06:39 p.m.) to March 05, 2020 (07:19 a.m.), from March 05, 2020 (03:59 a.m.) to March 06, 2020 (04:39 p.m.) and from March 06, 2020 (01:19 p.m.) to March 08, 2020 (01:59 a.m.). In the next step, 2 medium datasets of 5500 values were used. These sets consist data on Bitcoin open price of the periods from March 01, 2020 (00:00 a.m.) to March 04, 2020 (07:39 p.m.) and from March 04, 2020 (11:19 a.m.) to March 08, 2020 (06:59 a.m.). At the final stage, the whole time series (large dataset) containing 11000 values was considered. This set contains data on Bitcoin open price for the period from March 01, 2020 (00:00 a.m.) to March 08, 2020 (03:19 p.m.).

For small sets, the first 2000 values are used to train neural networks, the remaining 200 are used to estimate prediction accuracy. For medium and large data sets, this proportion remains unchanged: 90% for training; 10% to estimate forecasting accuracy. There is no unified method for determining the most appropriate number of neurons in networks. The network structure used in the work is purely experimental. The BP, RBF and ELM networks contain a single hidden layer consisting of 50 neurons, the LSTM network contain a single hidden layer consisting of 50 LSTM-cells. The size of sliding window is equal to 5. The number of training cycles for each network is 150.

Fig. 2-4 shows the results of predicting bitcoin rates over different periods for small, medium, and large datasets respectively. The actual data and data modeled by the ELM, RBF, BP and LSTM networks are represented in different dashed lines. Fig. 2 presents the forecast of Bitcoin open price for the second, third and fourth periods of small datasets. Fig. 3 demonstrates the forecast results for the second period of medium datasets in comparison with the actual data.

The Tabl. 1 presents a comparison of the average prediction accuracy for different length datasets and for all neural networks used.

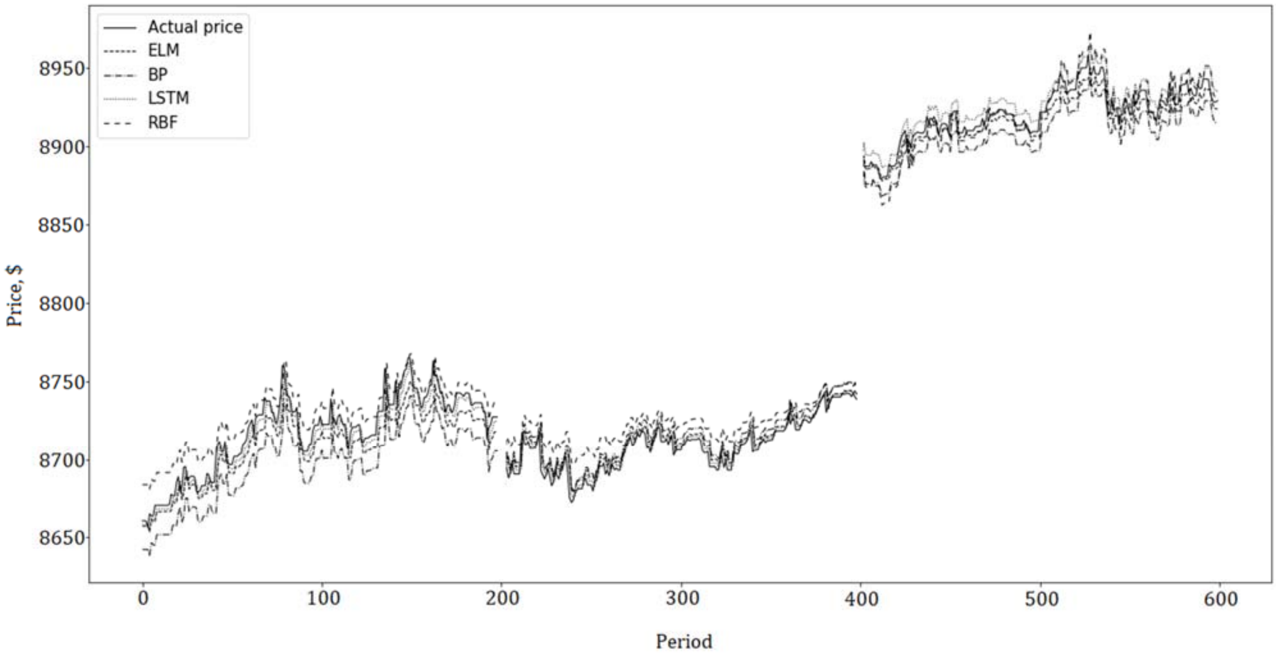

Fig. 2. Actual and predicted bitcoin exchange rate (small datasets)

Source: www.cryptodatadownload.com/data/gemini/, authorial calculation.

When forecasting on small datasets, the LSTM network has the smallest root mean square error and average absolute percentage error (7.1660 and 0.00063, respectively), outperforming all other networks by these indicators. The highest accuracy in predicting the direction of change of course have RBF-network (0.656) and LSTM-network (0.652).

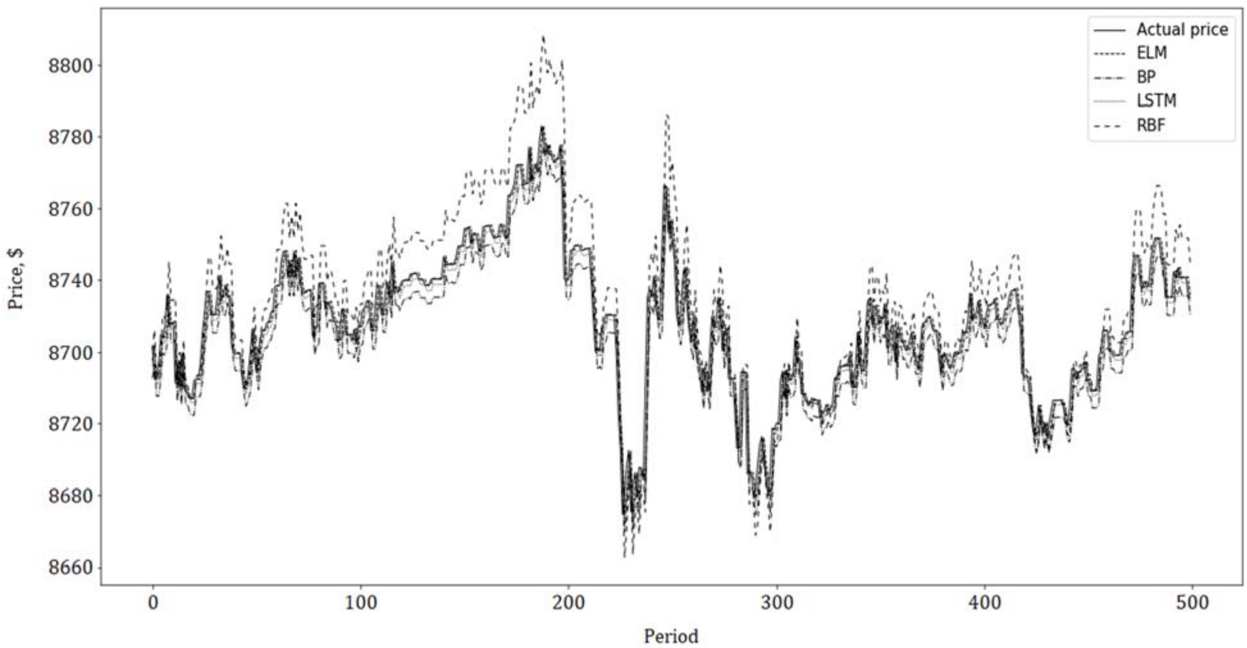

Fig. 3. Actual and predicted bitcoin exchange rate (medium datasets)

Source: www.cryptodatadownload.com/data/gemini/, authorial calculation.

The results show that the LSTM and ELM networks perform best when forecasting on medium datasets. They have the smallest root mean square errors (5.5119 and 5.6396, respectively) as well as the smallest values of the mean absolute percentage error (0.00043 and 0.00042). The RBF network and the ELM network showed the best results (0.629 and 0.622) in terms of forecasting accuracy.

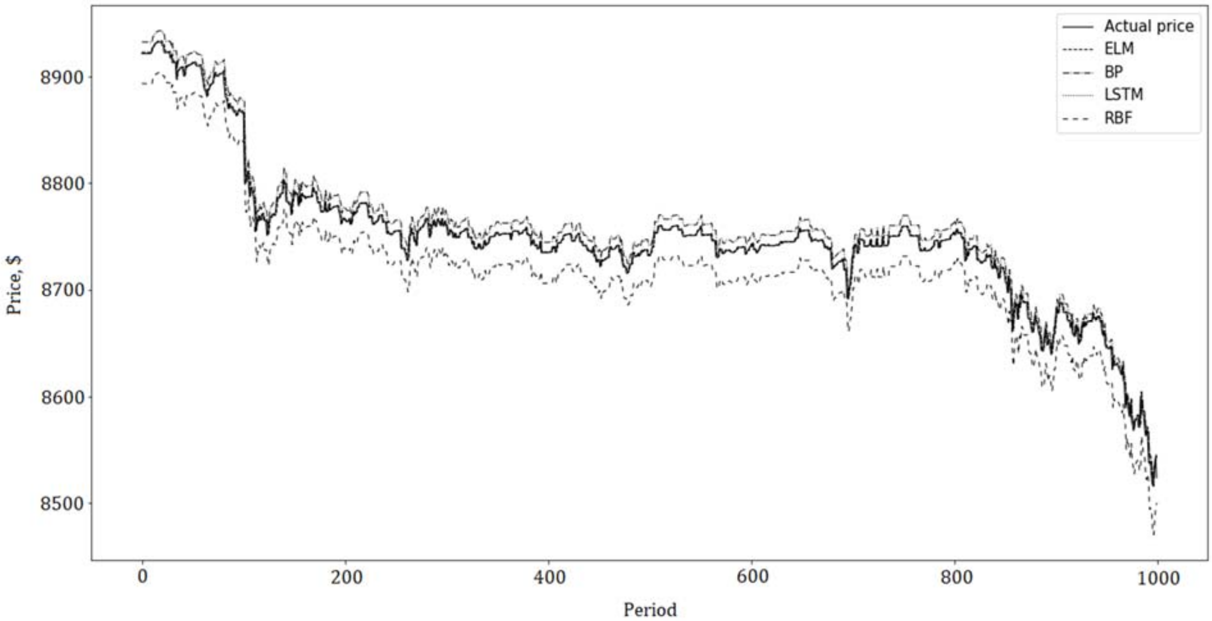

Fig. 4. Actual and predicted bitcoin exchange rate (large dataset)

Source: www.cryptodatadownload.com/data/gemini/, authorial calculation.

As for forecasting on a large dataset, the LSTM network performs best with the smallest root mean square error and mean absolute percentage error (5.3555 and 0.00035, respectively), ahead of the ELM network (5.4632 and 0.00035), RBF network (29.2583 and 0.00329) and the BP network (11.3947 and 0.00118). In predicting the direction of change of course, all networks showed approximately the same result with deviations in the difference at the level of statistical error.

Table **1. Estimations of prediction accuracy for different datasets**

		ELM	RBF	BP	LSTM
Small datasets	**RMSE**	9.9537	18.7067	12.4270	7.1660
	MAPE	0.00089	0.00195	0.00126	0.00063
	DA	0.610	0.656	0.594	0.652
Medium datasets	**RMSE**	5.6396	11.5808	8.2435	5.5119
	MAPE	0.00042	0.00113	0.00078	0.00043
	DA	0.622	0.629	0.567	0.583
Large dataset	**RMSE**	5.4632	29.2583	11.3947	5.3555
	MAPE	0.00035	0.00329	0.00118	0.00035
	DA	0.664	0.660	0.652	0.652

Source: www.cryptodatadownload.com/data/gemini/, authorial computation.

As you can see, the LSTM network has the best performance, especially in the case of forecasting on large datasets, due to the architectural features of this type of network. The RBF network showed almost identical good results for all datasets in terms of predicting the direction of change of course. However, the RBF network has the worst RMSE and MAPE values compared to the rest of the networks. The RMSE and MAPE values of ELM network are inferior to the LSTM network for all datasets, but for medium and large datasets the ELM network performs better results of DA.

Conclusion & Discussion.

In general, any deflationary collapse can be considered as price development of bitcoin. The onset of deflation may be associated with high job losses due to the coronavirus outbreak and the fall in oil prices. The prospect of a collapse in deflation has accelerated as oil prices plummet. However, the demand for cash may not have a significant negative impact on the price of bitcoin, as deflation will also increase the purchasing power of cryptocurrency. Increasing purchasing power is likely to lead to greater demand for bitcoin, as cryptocurrency is already being used as a means of payment.

Moreover, the appeal of cryptocurrency as a medium of exchange is likely to continue to increase as technology becomes more widespread in the daily lives of consumers caused by the pandemic coronavirus. In addition, if central banks are prepared to do whatever it takes to overcome deflation, real yields or inflation-adjusted bond yields are likely to remain negative or negligible at best. As a result, zero-yield assets such as gold and bitcoin can attract more buyers.

Predicting the behavior of the bitcoin market is challenging. The non-linear relationship between transaction data and unpredictable market fluctuations complicates forecasting. Exchange rate shifts and periodic drops in bitcoin exchange rates are also associated with numerous fraud cases, speculative transactions and market regulation issues. For example, in Germany, it is announced that from 2020, local banks will be allowed to offer the sale and storage of cryptocurrencies in accordance with new legislation. The new law may encourage investors to invest in cryptocurrencies, so bitcoin quotes have a chance of growth.

To demonstrate the impact of sample size on learning and network performance, we divided the sample into data sets of different lengths and compared the results obtained at each.

We have found that sample size affects forecasting results. The best results in bitcoin exchange rate modeling were demonstrated by the LSTM network. Particularly striking is its advantage when forecasting on large datasets. This fact is due to the deep architecture of this type of network. However, when studying time series, it is recommended to perform a comprehensive data analysis using appropriate networks, depending on the length of the series and the specificity of the database.

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ЗАСТОСУВАННЯ ШТУЧНОГО ІНТЕЛЕКТУ ДО МОДЕЛЮВАННЯ КУРСУ БІТКОЙНА

Штучні нейронні мережі – це сучасний метод, придатний для вирішення задачі апроксимації нелінійної залежності, що успішно застосовується у багатьох сферах. У цій статті порівнюються можливості прогнозування нейронних мереж зворотного поширення, радіально-базисних функцій, екстремальної машини навчання та довгої короткотермінової пам'яті, щоб визначити, який алгоритм штучного інтелекту найкращий для моделювання ціни біткойну. Критерієм порівняння продуктивності мережі було стандартне відхилення, середнє абсолютне відхилення та точність прогнозування напрямку зміни курсу. Разом із тим, при вивченні часових рядів рекомендується проводити комплексний аналіз даних, використовуючи відповідні мережі, залежно від довжини ряду та специфіки бази даних.

Ключові слова: штучний інтелект, зворотне поширення, радіально-базисні функції, екстремальна машина навчання, довга короткотермінова пам'ять, біткойн.

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ПРИМЕНЕННИЕ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА К МОДЕЛИРОВАНИЮ КУРСА БИТКОЙНА

Искусственные нейросети – это современный метод, пригодный для решения задач аппроксимации нелинейной зависимости, который успешно применяется во многих сферах. В этой статье сравниваются возможности прогнозирования нейронных сетей обратного распространения, радиально-базисных функций, экстремальной машины обучения, долгой краткосрочной памяти, чтобы определить, какой алгоритм искусственного интеллекта лучший для моделирования цены биткойна. Критерием сравнения производительности сети было стандартное отклонение, среднее абсолютное отклонение и точность прогнозирования направления изменения курса. Вместе с тем, при изучении временных рядов рекомендуется проводить комплексный анализ данных, используя соответствующие сети в зависимости от длины ряда и специфики базы данных.

Ключевые слова: искусственный интеллект, обратное распространение, радиально-базисные функции, экстремальная машина обучения, долгая краткосрочная память, биткойн.

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THE FUTURE OF MACROECONOMICS: A CYBERNETIC VIEW

This paper outlines many weaknesses in macroeconomic theory today and suggests a way out of the dilemma is to use systems or cybernetic thinking. The paper uses a topical case study to illustrate the authors' views of economics, cybernetics and mathematics. It concludes with recommendations for the future of economics in the 21st century.

Key words Economics, Cybernetics, Mathematics, Knowledge.

1. Introduction

Economics is a young subject, often dated to the publication of "The Wealth of Nations" by Adam Smith in 1776. (Smith 2012) and was an attempt to understand economic reality. Recently, there has been a groundswell of opinions about the poor state of Economics, both in theory and in practice. (Romer 2016, Hoover 2016, Mason. 2016). Among other things, Economics is accused of not being a Science, of using wrong assumptions, misusing mathematics and not being a reliable predictor of events. Some pertinent questions are:

a) Is Economics fulfilling its original purpose?

Is it possible to understand reality? Various views are discussed in section three.

b) Are the tools used adequate?

The major economic tool is mathematics and a prominent methodology is the creation of models., These are discussed in section five.

c) Are the hypotheses (assumptions) used correct?

Hypotheses can be incorrect for many reasons, for example, known facts have been ignored, misunderstood or subject to cultural bias. Such situations can be rectified but what is difficult to handle is when there is no awareness of what is missing – Rumsfeld's "unknown unknowns." (Rumsfeld, 2002)

d) What is the current state of Economic Modelling?

Mason considers Economists more engineers ("homo faber") than scientists ("homo sapiens")? Is their quest to understand how the economy works rather than what it is? (Mason, 2012) There is a difference between theory and practice, Current Economic theory is not interdisciplinary and must involve more research into communication, linguistics, communication, culture, psychology and neuroscience.

2. What is meant by Cybernetics?

The science of Cybernetics arose in the 1940's from the conferences that were sponsored by the Joshua Macey Foundation and ran from 1941 – 1960. Their aims were to pursue meaningful communication across scientific thinking and to unite Science. The first conference, which was entitled "Feedback Mechanisms and Circular Causal Systems in Biological and Social Systems" was attended by an unprecedented network of great minds at the time including Norbert Weiner who coined the word "Cybernetics" (taken from the Greek word "kubernētikós" meaning steersman).(Boem, 2017) It has been applied in the social sciences by many practitioners.

Cybernetics is the science of effective organization (Beer, 1985)

Underlying principles in the science of cybernetics are now discussed:

2.1. Structure causes Behaviour

A basic cybernetic principle is that "structure determines behaviour" (Beer, 1993) Structure is a stable form of interactions that allow people to operate together as a whole In embodied systems, people are constituted as roles. These roles transform disembodied relationships (meaning) into embodied relationships (identity, content and structure) One function of an economist is to determine the prevalent economic structure. This requires knowledge, erudition and experience.

2.2. Ashby's law of Requisite Variety

In the mechanised world, complexity can be roughly equated with size i.e. the more parts there are, the more complex it is. In a systems world, the complexity resides in the connections between the parts. Thus, a very small system can be highly complex – an example would be a