UDC 681.513.7; 519.688
DOI: 10.20535/SRIT.2308-8893.2023.2.02

THE ALGORITHM FOR PREDICTING THE CRYPTOCURRENCY RATE TAKING INTO ACCOUNT THE INFLUENCE OF POSTS OF A GROUP OF FAMOUS PEOPLE IN SOCIAL NETWORKS

P. BIDYUK, O. GAVRILENKO, M. MYAGKYI

Abstract. This article presents an algorithm for predicting the rate of a selected cryptocurrency, taking into account the posts of a group of famous people in a particular social network. The celebrities chosen as experts, i.e., famous personalities whose posts on social networks were studied, are either familiar with the financial industry, particularly the cryptocurrency market, or some cryptocurrency. The dataset used was the actual rates of the cryptocurrency in question for the selected period and the statistics of expert posts in the selected social network. The study used methods such as the full probability formula and the Bayesian formula. It was found that posts by famous people on social media differently affected cryptocurrency rates. The "main" expert was identified, and his posts were used to forecast the selected cryptocurrency's rate.

Keywords: cryptocurrency exchange rate, forecasting algorithms, social media posts, group of experts, "main" expert, information technology of intelligent analysis.

INTRODUCTION

The study of cryptocurrency changes is gaining more and more popularity every day due to the relative ease of entry and the abundance of recommendation information regarding the process. Buying and selling cryptocurrencies is a rather interesting process, since, if certain conditions are met, you can increase your wealth several times, or even replace your main job with this business. However, in order to really make money on this process, it is necessary to conduct research on the chosen cryptocurrency, exchange and news related to them.

The relevance is due to the growing popularity of investing in cryptocurrencies. Publications of famous people who have a vested interest in this process have a significant impact on the price formation of certain cryptocurrencies. When traders create forecasts of changes in the exchange rate of certain cryptocurrencies, they will need a recommendation information system that can analyze the impact of such publications on cryptocurrency changes, which will increase the accuracy of the forecast.

The obtained forecasts can be used by financial market participants to obtain high-quality forecasts of cryptocurrency rates, on the basis of which they will make decisions on its purchase (sale).

LITERATURE ANALYSIS AND PROBLEM STATEMENT

The task of analyzing publications from the Internet is very important, since a well analyzed publication can provide a lot of different information.

Article [1] discusses the process of computer based detection and categorization of opinions expressed in a piece of text to determine whether the writer's attitude towards a particular topic, product, etc. is positive, negative, or neutral. A detailed study of sentiment analysis and its cause-and-effect relationship. Using sentiment analysis, you can get a generalized event based on mood and time. On the other hand, the use of causality will be useful not only for determining the causes and effects, respectively, but also for their further forecasting. The main part of the article is an overview of the combination of these two approaches, which degenerates into a model that allows to determine the mood for future events, as well as to create a temporal forecast of the time that will pass between certain events. To assess the accuracy, we used the following statistic: average relative error.

To view publications, you need to choose a place where there are the most of them and they are in a single text format, for this purpose Twitter is a good messenger, work [2] discusses in detail the special linguistic analysis and statistics of Twitter. This study aimed to identify criminal elements in the United States by modeling topics of discussion and then incorporating them into a crime prediction model. Thus, the study was conducted on the impact of social media posts on future crimes.

In [3], methods for predicting user ratings of individual items using probabilistic algorithms were considered. In fact, the article perfectly illustrates the existence of computational patterns in terms of what exactly network users like under certain circumstances. In other words, this study emphasizes the impact of probabilistic algorithms in the field of recommender systems, and provides an overview of key methods that have been successfully applied. The considered algorithms for object classification allow solving the problem of predicting user evaluation of content and its categorization, as well as improving existing methodologies for building information systems.

Article [4] is quite relevant today due to the difficult epidemiological situation in the world. It analyzed microblogs on Twitter and proposed several methods for identifying messages. It was determined that over ten weeks of more than five hundred thousand reports, their best model achieved a correlation of 0.78 with CDC statistics.

It is also necessary to highlight Internet blogs, where many people express their own opinions and visions of certain problems, etc. Therefore, in [5], a study was conducted to identify hate groups. The proposed approach is semi-automatic and consists of four modules, namely: blog spider, information retrieval, network analysis, and visualization. The study was conducted on the Xanga blog site. The results of the analysis were to identify some interesting demographic and topological characteristics in hate groups and to identify at least two large communities in addition to smaller ones. The proposed approach is also appropriate for studying hate groups and other related communities on blogs.

For business, the process of analyzing large amounts of data and understanding the needs of most people is very important, as it directly affects the company's revenue. Article [6] provides a constructive consideration of the problem of business accumulation of large amounts of data and the problems of their intellectual processing. The author provides a clear definition and explanation of the terms "data mining" and "data intelligence". As a result, an objective conclusion was made about the expediency of using data mining to increase the competitiveness of enterprises.

It should be noted that all of the above works describe the methods used in our study, but do not provide the results of forecasting currency rates, including cryptocurrencies. Accordingly, the factors that influence them were not studied.

In [7], the authors study the main macroeconomic indicators of influence on the US dollar exchange rate in Ukraine: purchase/sale of cash currency, purchase/sale of non-cash currency, balance of purchase/sale of cash and non-cash currency, current year inflation, nominal and real GDP, purchase/sale by bank customers, transactions between banks, gross and net international reserves, unemployment rate, discount (interest) rate, balance of foreign exchange interventions, and volume of transactions of nominal value. The main economic components of exchange rate formation were identified using the principal components method. Using the statistical models ARIMA, Exponential Smoothing and SSA, the values of the selected factors of influence are predicted. The values of exchange rates are forecasted using regression models built by Fast Tree, Fast Forest, Fast Tree Tweedie and Gam algorithms, and the obtained values are tested for accuracy. This article did not forecast cryptocurrency rates specifically and did not study the impact of such a factor as publications in social media.

Article [8] analyzes the methods, areas of application, and approaches to analyzing publications and forecasting events based on the collected data, and also gives the concept of the impact of publications on changes in the cryptocurrency rate. The relevance of the topic is substantiated and the possibilities of appropriate application of the results of the work are described. The main stages of working with event forecasting data are identified, namely: data pre-processing, further analysis and forecasting. This article did not investigate the level of influence of celebrity publications on social media on the cryptocurrency rate. In addition, we considered forecasts based on the posts of only one expert.

Within the framework of the studies cited in [7, 8], information systems were created to implement the above tasks of data mining.

Studies have shown that celebrity posts do have a significant impact on cryptocurrency rates. This can be easily verified using classical statistical analysis tools, in particular, by analyzing the correlations between real and predicted cryptocurrency rates. However, it should be noted that each famous personality – hereinafter referred to as an expert – has a different level of awareness in the financial sector, and is also involved in the process of forming cryptocurrency rates in different ways (i.e. some experts are directly related to a particular cryptocurrency, and some are not), so the level of their influence on the forecasted rate will be different. Therefore, it is advisable to study the level of influence of different experts on the forecasted cryptocurrency rates in order to further rank them. This study will improve the accuracy of cryptocurrency rate forecasts.

The following are recommended as ranking parameters:

1) the number of posts of a particular famous person in social networks for the period under consideration;

2) the accuracy of the forecasts obtained for each expert in relation to the actual cryptocurrency rate;

3) deviations from the respective forecasts obtained without taking into account social media posts.

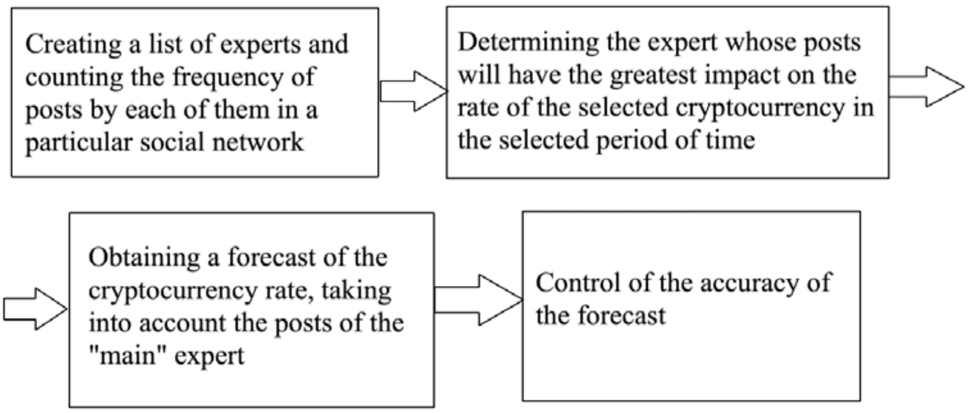
In this article, the number of posts for each of the pre-selected well-known persons in social networks for the period under consideration is taken as such a parameter.

PURPOSE AND OBJECTIVES OF THE STUDY

The purpose of the study is to develop an algorithm for predicting the cryptocurrency rate based on the posts of a group of famous people in social networks.

- This will make it possible to increase the reliability of cryptocurrency rate forecasting.
- To achieve this goal, the following tasks were set:
- create a list of experts and calculate the frequency of posts by each of them in a particular social network;
- to identify the expert whose posts will have the greatest impact on the rate of the selected cryptocurrency in a selected period of time;
- to obtain a forecast of the cryptocurrency rate taking into account the posts of the “main” expert;
- control the accuracy of the forecast.

Figure shows the process of calculating the rate forecast for the selected cryptocurrency:



The process of calculating the cryptocurrency rate forecast

MATERIALS AND METHODS OF THE STUDY

The object of the study is the forecast of cryptocurrency rates.

The information required to analyze the level of influence of social media posts on cryptocurrency rates is a list of experts whose level of influence will be studied, the time interval of the study, the number of posts made by each of the experts in question during the specified period of time, as well as the actual cryptocurrency rates for the relevant period.

The use of mathematical tools based on the full probability and Bayesian formulas allows us to use this information to determine the expert who is more likely to make posts during the period under consideration. We will call this expert the "main" expert.

So, the following information is required as input: a list of experts, the number of posts by each expert, and the real rates of the selected cryptocurrency for the period under consideration.

Table 1. Fragment of the input data

Hours	Real courses
1	467
2	475
3	516
4	533
5	508
6	510
7	525
8	512
9	514
10	514

Table 2. Fragment of input data (continued)

Expert	Number of posts	Number of posts related to cryptocurrency
Expert 1	9	6
Expert 2	7	5
Expert 3	4	2

Experts were selected as well-known personalities who are either knowledgeable in the field of finance in general and cryptocurrencies in particular, or whose activities are somehow related to a particular cryptocurrency, or not.

A fragment of the dataset is shown in Table 1. Table 1 shows the real rates of the selected cryptocurrencies, which were taken from the website of the Binance crypto exchange [9].

Table 2 shows the number of posts by the selected experts in 10 hours on the social network.

The data generated in this way is the input for this study. As part of the study, it is necessary to:

- create a list of experts and count the number of their posts on social media;
- determine the "main" expert using the Bayesian formula;
- to obtain a forecast of the cryptocurrency rate, taking into account the posts of the "main" expert, based on the approach described in [8].
- to calculate the accuracy of MAPE forecasts.

The use of these methods guarantees reliable results when predicting cryptocurrency rates and studying the level of influence on them by posts of famous people in social networks.

To conduct statistical analysis and obtain results based on these methods, the corresponding software was developed.

ALGORITHM FOR TAKING INTO ACCOUNT THE LEVEL OF INFLUENCE OF POSTS BY SEVERAL FAMOUS PEOPLE IN SOCIAL NETWORKS ON THE CRYPTOCURRENCY RATE

Forming a list of experts and counting the frequency of posts by each of them in a particular social network

Task statement. From the set of users of a social network, we select a subset $A = (a_1, a_2, \dots, a_n)$ of users who satisfy the following requirements:

1) the users are famous persons;

2) they are active users of the social networks and have a large number of subscribers;

3) they`ll have different primary professional interests;

4) all pairs of users a_i and a_r, $i, r = 1, 2, \ldots, n$, do not maintain communication in the network (they are not friends, do not respond to each other's posts).

We call such users experts.

Suppose that over a certain period of time, experts have made m posts in a social network, and k of them are related to a certain cryptocurrency. We consider the context of the posts to be arbitrary. For the specified period of time, expert a_1 published m_1 posts, of which k_1 posts are related to a certain cryptocurrency, expert a_2 published m_2 posts, of which k_2 posts are related to a certain cryptocurrency, … , expert a_n published m_n posts, of which k_n posts are related to a certain cryptocurrency:

$$m_1 + m_2 + \ldots + m_n = m;$$

$$k_1 + k_2 + \ldots + k_n = k,$$

where $m_1, m_2, \ldots, m_n$ are the frequencies of expert posts; $k_1, k_2, \ldots, k_n$ are the frequencies of expert posts related to a particular cryptocurrency, where i is the number of the expert, $i = 1, 2, \ldots, n$.

It is necessary to calculate the frequencies of posts of all selected experts for an arbitrary time interval [10].

Rationale. This choice of experts is due to the need to form the set of such experts who will be independent of each other both in the space of the chosen social network and in the professional space.

Results. From the data presented in Table 2, it can be seen that the considered set of 3 experts A = (expert 1, expert 2, expert 3). According to the social networks data, it is known that $m = 20$ posts were published over a period of 10 hours, with $k = 13$ posts related to the selected cryptocurrency: $m_1 = 9$, $m_2 = 7$, $m_3 = 4$, and $k_1 = 6$, $k_2 = 5$, $k_3 = 2$.

Determining the expert whose posts will have the greatest impact on the rate of the selected cryptocurrency in a selected period of time

Task statement. Based on the list of experts $A = (a_1, a_2, \ldots, a_n)$ obtained in section 1 and taking into account the frequencies of their posts in the selected social network for a specified small period of time — $m_1, m_2, \ldots, m_n$, and $k_1, k_2, \ldots, k_n$, it is necessary to determine the "main" expert.

The formulated problem can be easily interpreted as a classical probabilistic problem: *m* posts were written in a certain period of time. It is known that *n* experts published posts during this period, where $m_1, m_2, \ldots, m_n$ are the frequencies of expert posts, $k_1, k_2, \ldots, k_n$ are the frequencies of expert posts related to the chosen cryptocurrency, where *i* is the number of the expert, $i = 1, 2, \ldots, n$. Action *A* is that in an arbitrary period of time someone wrote the post related to the selected cryptocurrency. It is necessary to determine which expert is more likely to have made this post [11].

Rationale:

$A =$ (the post related to the selected cryptocurrency was written at any time t from the interval [0;T]),

$H_1 =$ (the post was written by expert 1),

$H_2 =$ (the post was written by expert 2),

...

$H_n =$ (the post was written by expert n).

We assume that actions H_i are pairwise independent, where i is the number of the expert, $i = 1, 2, \ldots, n$. These assumptions can be made based on a list of requirements that experts must meet (see section 1).

According to the full probability formula:

$$P(\mathrm{A}) = \sum_{i=1}^{n} P(H_i) P(A / H_i), \tag{1}$$

where

$$P(H_i) = \frac{m_i}{m}, \tag{2}$$

where m_i is the number of publications made by the expert i, and k_i is the number of publications made by the expert i related to the selected cryptocurrency, m is the total number of publications for the period $[0;T]$, $P(H_i)$ is the probability that the post was published by expert i, $P(A/H_i)$ is the probability that at any point in time t the post related to the selected cryptocurrency was written, provided that the post was written by expert i, $i = 1, 2, \ldots, n$.

Then, using the Bayesian formula, we calculate the probability for each expert that he or she made the post, if it is known that the post was made during the period under consideration:

$$P(H_i / A) = \frac{P(H_i) P(A / H_i)}{P(A)}, \tag{3}$$

where $P(H_i)$ is the probability that the post was published by expert i, $P(A/H_i)$ is the probability that at any point in time t the post related to the selected cryptocurrency was written, provided that the post was written by expert i, $P(H_i /A)$ is the probability that the post was written by expert i, provided that it is known that at any point in time t the post related to the selected cryptocurrency was written.

Among the obtained a posteriori probabilities, the highest one is chosen. This means that this expert is most likely to have published a post in the time period under consideration and thus will have a greater impact on the rate of the selected cryptocurrency. It is this expert that will be considered the “main” expert for the forecasted time period $[T; T + \Delta t]$. This is due to the fact that the influence of the posts made during the time period $[0;T]$ also extends to a certain time period $[T; T + \Delta t]$.

It should also be noted that the obtained a posteriori probabilities can be further used to find average estimates of the effectiveness of predictive adaptive algorithms for changing the cryptocurrency rate under the influence of the sequential appearance of individual or group posts of experts over time. The creation of such algorithms and, as a result, the corresponding intelligent technologies is the subject of further research by the authors.

Result. As mentioned in section 1, according to the data presented in Table 2, we consider the set of 3 experts $A =$ (expert 1, expert 2, expert 3). According to the social networks data, it is known that 20 posts were published during a period of 10 hours, 13 posts related to the selected cryptocurrency, with $m_1 = 9,\ m_2 = 7,\ m_3 = 4$ and $k_1 = 6,\ k_2 = 5,\ k_3 = 2$.

According to formula (2):

$$P(H_1) = \frac{9}{20},\ P(H_2) = \frac{7}{20},\ P(H_3) = \frac{4}{20},$$

$$P(A / H_1) = \frac{6}{9},\ P(A / H_2) = \frac{5}{7},\ P(A / H_3) = \frac{2}{4}.$$

According to formula (1)

$$\mathrm{P}(A) = \frac{6}{20} + \frac{5}{20} + \frac{2}{20} = \frac{13}{20}.$$

According to formula (3):

$$P(H_1 / A) = \frac{6}{13},\ P(H_2 / A) = \frac{5}{13},\ P(H_3 / A) = \frac{2}{13},$$

so, with probability of $\frac{6}{13}$ the post was most likely made by expert 1. Therefore, he was considered the “main” expert for this period of time. The next expert is expert 2 according to the probability of $\frac{5}{13}$, and the last one is expert 3 according to the probability of $\frac{2}{13}$.

Obtaining a forecast of the cryptocurrency rate taking into account the posts of the “main” expert

Task statement. Let the set of rates of the selected cryptocurrency for the time period $[0;T]$ be known as the set $X = \{x_t\}$, $t \in [0;T]$. You need to get the set of forecasts of the cryptocurrency rates taking into account the “main” expert chosen in section 1 for the period $[T;T + \Delta t]$ as the set $Y = \{y_t\}$, $t \in [T;T + \Delta t]$.

Rationale. To obtain forecasts, we will use the ATAPSN (algorithm for taking into account posts in social networks), taking into account the posts of the “main” expert [8].

The idea of the algorithm is to calculate the coefficient of significance of the posts of the “main” expert c_t, at time *t* from the interval $[T;T + \Delta t]$, which is calculated by the formula:

$$c_t = \delta_t \cdot ch_t, \tag{4}$$

where ch_t is the tone of the “main” expert’s post:

$$ch_t = \begin{cases} 1, \text{ if the post is positive}, \\ 0, \text{ if the post is neutral}, \\ -1, \text{ if the post is negative}, \end{cases} \quad (5)$$

δ_t is the accuracy of the previous forecast,

$$\delta_t = |y_t - x_t|, \quad (6)$$

where y_t is the predicted value of the cryptocurrency exchange rate obtained without taking into account posts on social networks, x_t is the actual value of the cryptocurrency exchange rate, where t is the point in time.

After determining the coefficient c_t from (4)–(6), a forecast of cryptocurrency exchange rate changes will be created based on the available data for the period of time.

$$y'_{t+1} = y_{t+1} + c_t .$$

Result. For the "main" expert identified in section 2, expert 1, a 10-hour forecast of the selected cryptocurrency rate was obtained (see Table 3).

Table 3. Forecast of the selected cryptocurrency rate for the expert 1

Hours	Forecast rates
1	466.19
2	473.44
3	513.78
4	534.78
5	508.31
6	508.6
7	525.67
8	510.85
9	512.55
10	515.43

Control of the accuracy of the obtained forecast

Task statement. For each of the experts selected in section 1, based on the ATAPSN algorithm (see section 3), we made a forecast of the rate of the selected cryptocurrency and indicated the actual rate for the period of time under consideration. The resulting forecasts, along with the actual cryptocurrency rates, are provided in the input dataset (see Table 1).

Based on the input dataset, the following statistical samples X, Y_j $(j = \overline{1,3})$ of size s each (where s is the number of forecasts made at the selected time point) should be formed:

X — the set of real cryptocurrency rates;

Y_1 — the set of predicted cryptocurrency rates obtained using the ATAPSN, taking into account expert 1 posts;

Y_2 — the set of predicted cryptocurrency rates obtained using the ATAPSN, taking into account expert 2 posts;

Y_3 — the set of predicted cryptocurrency rates obtained using the ATAPSN, taking into account expert 3 posts.

For each expert, it is necessary to calculate the accuracy of the MAPE forecast.

Rationale. The average relative sampling error is calculated by the formula:

$$\mathrm{MAPE}_j = \frac{1}{s}\sum_{l=1}^{s}\frac{\left|x_l - y_{jl}\right|}{x_l}100 .$$

where x_l are sample items X, y_{jl} are sample items Y_j, $j=(\overline{1,3})$, $l=(\overline{1,s})$ is the volume of samples X and Y_j [12].

Using this measure of forecast accuracy will allow us to control the quality of the dataset and rank experts in terms of the accuracy of forecasts obtained from their posts (see Table 4).

Table 4. Level of model adequacy

MAPE, %	**Forecast accuracy**
less than 10	High
10–20	Good
20–40	Satisfactory
40–50	Poor
more than 50	Unsatisfactory

Totally, these values are dependent on the purpose of the forecast. It is up to the researcher to set the limits of the accuracy indicator that satisfy him or her.

In case of low accuracy of the forecast, it is recommended to make changes to the significance factor to make the analysis of further changes more accurate (see section 3).

Result. For samples $Y_1 - Y_3$, we obtain the following values for the coefficients MAPE_j (see Table 5).

Table 5. Values of thecoefficiennts MAPE

X	Y_1	Y_2	Y_3
467	466.19	497.8707174	502.2597
475	473.44	502.1439974	463.9021
516	513.78	506.4172773	490.0742
533	534.78	510.6905573	515.4008
508	508.31	514.9638372	523.135
510	508.6	519.2371172	528.5218
525	525.67	523.5103971	518.3018
512	510.85	527.7836771	515.8382
514	512.55	532.056957	529.6971
514	515.43	536.330237	521.8438
MAPE_j	0.23406855	3.27736587	3.1429464

Table 5 shows that sample Y_1 has the lowest MAPE (0.23%), the next sample Y_3 (3.14%), and the biggest error is in sample Y_2 (3.28%). It should be noted that the accuracy of all forecasts is high, according to Table 4, which indicates the quality of the built forecasting model.

According to the results obtained, it can be stated that in terms of forecast accuracy, expert 1 has the most significant posts, next expert 3, and finally expert 2. The results are fully consistent with the fact that expert 1 was chosen as the "main" expert, whose forecasts are the most significant.

CONCLUSIONS

In this article, we presented a modification of the ATAPSN algorithm [8], which allows taking into account the posts of a group of pre-selected experts and form a list of requirements for them.

This approach allows to increase the accuracy of forecasts of the selected cryptocurrency rates, which has been confirmed statistically.

This approach calculates the a posteriori probabilities that a post related to the selected cryptocurrency was written by a particular expert during the forecasting interval. They were used to determine the "main" expert.

The obtained a posteriori probabilities can be further used to find average estimates of the efficiency of predictive adaptive algorithms for changing cryptocurrency rates under the influence of the sequential appearance of individual or group posts by experts. The creation of such algorithms and, as a result, the corresponding intelligent technologies is the subject of further research by the authors.

It should be noted that there may be different "main" experts at different time intervals.

To use this approach, it is recommended to consider small time intervals, each of which allows you to more accurately determine your "main" expert. This increases the accuracy of forecasts of the selected cryptocurrency rates over the entire time interval.

Using the post frequencies in social networks as a parameter for determining the influence of experts allows us to apply the classical apparatus of probability theory, which guarantees the correctness of the results obtained.

The disadvantages include the fact that the accuracy of the forecast may be negatively affected by an unsuccessfully selected time interval for which the forecast was made, since it is not known in advance how long an expert's post will be affecting the cryptocurrency rate. This indicates the need for the constant monitoring of both cryptocurrency rates and expert posts on social networks.

The proposed algorithm is an intermediate step towards the creation of a multi-expert model for forecasting cryptocurrency rates.

REFERENCES

1. P. Preethi, V. Uma, and A. Kumar, "Temporal Sentiment Analysis and Causal Rules Extraction from Tweets for Event Prediction," *Procedia Computer Science*, no. 48, pp. 84–89, 2015. Available: https://doi.org/10.1016/j.procs.2015.04.154
2. Matthew S. Gerber, "Predicting crime using Twitter and kernel density estimation," *Decision Support Systems*, no. 61, pp. 115–125, 2014. Available: https://doi.org/10.1016/j.dss.2014.02.003
3. O.V. Gavrilenko and I.V. Kuptsova, "Research of tasks of estimation of objects in computer social networks by means of reliable algorithms [Text]," *materials of the 8th international scientific and technical conference "Modern directions of development of information and communication technologies and means of management", Kharkiv, April 26–27, 2018*, pp. 67–68.
4. A. Culotta and B. Huberman, "Towards detecting influenza epidemics by analyzing Twitter messages," *Proceedings of the First Workshop on Social Media Analytics, ACM, 2010,* pp. 115–122.
5. M. Chau and J. Xu, "Mining communities and their relationships in blogs: A study of online hate groups," *J. Hum.-Comput. Stud.*, 65(1), pp. 57–70, 2007.
6. O.V. Gavrilenko, "Review of methods of hybridization of intellectual information processing," *Scientific Bulletin of Kherson State University, series "ECONOMIC SCIENCES"*, issue 8, part 3, p. 1, pp. 204–207, 2014.
7. O.V. Gavrylenko, K.D. Novakivska, and O.A. Shumeiko, "Selection of the most influential economic factors for forecasting the US dollar exchange rate," *NTU Bulletin*, no. 54, pp. 26–35, 2022. doi: 10.33744/2308-6645-2022-4-54-026-035.
8. O. Gavrylenko, M. Miahkyi, and Y. Zhurakovskyi, "The task of analyzing publications to build a forecast for changes in cryptocurrency rates," *Adaptive Automatic Control Systems*, vol. 2, no. 41, pp. 90–99, 2022. Available: https://doi.org/10.20535/1560-8956.41.2022.271349
9. *Binance cryptocurrency exchange.* [Online]. Available: https://www.binance.com/en/strategy/spot/grid/DOGEUSDT. Accessed on: 20 April 2023.
10. M.V. Kartashov, *Probability, processes, statistics*. Kyiv: VPC Kyiv University, 2007, 504 p.
11. V.P. Denysiuk, V.M. Bobkov, T.A. Pogrebetska, and V.K. Repeta, *Higher mathematics. P4. Probability theory and mathematical statistics*. Kyiv: NAU-druk, 2009, 256 p.
12. *Time series*. [Online]. Available: https://kstat.pnu.edu.ua/wpcontent/uploads/sites/63/2018 /04/%D0%A7%D0%B0%D1%81%D0%BE%D0%B2%D1%96-%D1%80%D1%8F%D0%B4%D0%B8.pdf. Accessed on 20 April 2023.

Received 01.05.2023

INFORMATION ON THE ARTICLE

Petro I. Bidyuk, ORCID: 0000-0002-7421-3565, Educational and Research Institute for Applied System Analysis of the National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Ukraine, e-mail: pbidyuke_00@ukr.net

Olena V. Gavrilenko, ORCID: 0000-0003-0413-6274, National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Ukraine, e-mail: gelena1980@gmail.com

Mykhailo Yu. Myagkyi, ORCID: 0000-0002-8038-8839, National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute”, Ukraine, e-mail: mishamyagkiy3@gmail.com

АЛГОРИТМ ПРОГНОЗУВАННЯ КУРСУ КРИПТОВАЛЮТИ З УРАХУВАННЯМ ВПЛИВУ ДОПИСІВ ГРУПИ ВІДОМИХ ЛЮДЕЙ В СОЦІАЛЬНИХ МЕРЕЖАХ / П.І. Бідюк, О.В. Гавриленко, М.Ю. Мягкий

Анотація. Наведено алгоритм прогнозування курсу обраної криптовалюти, з урахуванням дописів групи відомих особистостей в конкретній соціальній мережі. Експертами з-поміж них обирали ті, чиї дописи в соціальних мережах досліджувалися, та які обізнані з галуззю фінансів, зокрема з ринком криптовалют, або так чи інакше з певною криптовалютою. Як датасет використано реальні курси криптовалюти за обраний період часу та статистику дописів експертів в обраній соціальній мережі. У межах дослідження застосовано такі методи, як формула повної ймовірності та формула Баєсса. З’ясовано, що дописи відомих людей в соціальних мережах по-різному впливають на курси криптовалют. Визначено «основного» експерта з урахуванням дописів якого отримано прогноз курсу обраної криптовалюти.

Ключові слова: курс криптовалюти, алгоритми прогнозування, пости в соціальних мережах, група експертів, «головний» експерт, інформаційна технологія інтелектуального аналізу.