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FORECASTING THE CRYPTOCURRENCY EXCHANGE RATE BASED ON THE RANKING OF EXPERT OPINIONS

To date, most existing cryptocurrency exchanges do not have in their arsenal tools that would allow them to verify and investigate the information disseminated on social networks regarding a particular cryptocurrency. This makes it possible to conduct a relevant research with the subsequent development of a tool that, if used correctly, will provide users with advisory advice on further actions in relation to the cryptocurrency under study in the system. Based on this advice, interested parties will be able to adjust their decisions regarding further financial steps. The basis of most recommender systems is always the need to identify some influencing factors, which are later given certain weights to facilitate and simplify the formulation of further advice for users. In this paper, we study the influence of celebrity publications on the formation of prices for a particular cryptocurrency at a certain point in time. The importance and existence of this influence was previously proven by statistical methods. **The purpose of the study** is to develop an algorithm for studying the level of influence of posts of each of the selected group of experts in social networks on the cryptocurrency rate. **The object of the study** is the forecast of cryptocurrency rates. The input data used were the 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 over the specified period of time, and the actual cryptocurrency rates for the relevant period. The experts were 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. **Research methods.** Experts are ranked based on the full probability and Bayesian formulas. Forecasting of cryptocurrency rates in a selected period of time is carried out using the algorithm for forecasting cryptocurrency rates based on expert posts on social networks (ATAPSN). To control the accuracy of forecasts, the relative average error is calculated. Recommendations for financial transactions with cryptocurrencies are formed by entering the critical value of the exchange rate and calculating the arithmetic mean of cryptocurrency exchange rates for a specified period of time. **Results.** As a result of the research, an algorithm has been developed that allows taking into account the impact of the posts of each of the selected ranked group of experts on changes in the rates of a particular cryptocurrency. On the basis of the obtained forecasts, the paper presents a methodology for forming recommendations for financial transactions with them.

Keywords: cryptocurrency exchange rate; forecasting algorithm; social media posts; ranking of a group of experts; information technology of intellectual analysis.

1. Introduction

At the moment, there are a huge number of publications and various information on various cryptocurrencies, which leads to a constant growth in the popularity of this topic among all age groups. This is due to the relative ease of entering cryptocurrency exchanges for further interaction with cryptocurrencies. Users of most cryptocurrency exchanges are provided with a fairly wide range of financial transactions and other opportunities. The simplest and therefore the most popular are buying and selling cryptocurrencies. These operations require minimal skills from the user, but they also do not have high liquidity. That is, the exchange does not provide users with conditions for rapid enrichment through the use of basic skills. However, developers and owners of cryptocurrencies are interested in the widest possible distribution of their own products, so exchanges, in turn, try to encourage people to use more "advanced" technologies and opportunities provided by the system. Certain tools allow you to analyze the state of the market in relation to a selected cryptocurrency and thus formulate a theory about its future course. These information manipulations, once disseminated on social media, encourage many users to take appropriate action.

Thus, the relevance of this study is due to the growth of an already large amount of information about cryptocurrencies, which is aimed specifically at encouraging people to take appropriate actions in relation to certain cryptocurrencies.

However, most of the existing cryptocurrency exchanges currently do not have tools in their arsenal that would allow them to verify and investigate the information disseminated on social media regarding a particular cryptocurrency. This allows us to conduct a relevant study with the subsequent development of a corresponding tool that, if used correctly, will provide users with advisory advice on further actions regarding the cryptocurrency under study in the system. Based on

this advice, interested parties will be able to adjust their decisions regarding further financial steps.

Most recommender systems are always based on the need to identify certain factors of influence, which are later given certain weights to facilitate and simplify the formulation of further advice for users.

In our case, it is the influence of publications of famous people on the formation of prices for a certain cryptocurrency at a certain point in time that is being studied. The importance and existence of this influence has been proven by the authors of this paper in previous studies.

2. Literature review and problem statement

In general, the collection and processing of data from publications on cryptocurrencies from social networks and other online information platforms is a rather significant task, as they can provide a lot of useful and comprehensive information that will be necessary to build a high-quality mathematical model for further forecasting.

Paper [1] discusses the process of computer detection and categorization of opinions expressed in a piece of text in order to determine whether the writer's attitude toward a particular topic, product, etc. is positive, negative, or neutral. In the present study, a detailed study was conducted: sentiment analysis and its cause-and-effect relationship. Also, with the help of sentiment analysis, a generalized event was determined on its basis and taking into account the time. The results of the analysis of the cause-and-effect relationship can be used not only to determine the causes and effects, but also to further predict user sentiment. The main part of the publication is an overview of the combination of these approaches, which are combined into a single model that allows you to determine the mood during future events, as well as create a time forecast for the length of the interval between certain events. The average relative error was used to assess the accuracy.

To search for publications that meet certain requirements, such as the number, a single text format, and others, you need to select a specific social network. Twitter (currently X) meets the requirements well, and work [2] describes in detail the special linguistic analysis and statistics in this social network. The main purpose of the study, the authors noted, was to identify criminal elements in the United States by modeling topics of discussion and then incorporating them into a crime prediction model. A thorough analysis of the impact of publications in social networks on the potential for certain criminal acts to occur in the future was conducted.

Paper [3] provides a comprehensive reference for researchers and practitioners, covering all areas that contribute to the construction and analysis of social networks.

Paper [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, out of more than five hundred thousand reports, the best model achieved a correlation of 0.78 using the CDC statistical method.

Also, one should not miss online blogs, where many people express their own opinions and visions of certain problems. 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 and the financial market, the process of analyzing large amounts of data and understanding the needs of the majority of people is very important, as it directly affects the income of the company and individuals. The research conducted in [6] was aimed at identifying the dominant factors that lead to currency crises. Also, this publication is intended to identify and characterize currency crises, as well as to predict the potential occurrence of the latter at an early stage. This will save managers some time to improve their crisis management policies and adjust their responses.

Paper [7] investigated the dynamics of linear and nonlinear, serial dependencies in financial time series within a moving window. In particular, attention is focused on identifying episodes of statistically significant two- and three-point correlation in the returns of several leading exchange rates, which may offer some potential for their predictability. The moving window approach was used to capture the dynamics of correlation for different window lengths and to analyze the distribution of periods with statistically significant correlations. It was found that for sufficiently large window lengths, these distributions correspond well to a power law.

The predictability itself is measured by the hit rate, i.e., the level of consistency between the actual return features and their predictions obtained using a simple correlation-based predictor.

It should be noted that all of the above studies are general in nature and do not provide results of forecasting currency rates, including cryptocurrencies. Accordingly, the factors that influence them were not investigated.

In [8], 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 work did not forecast cryptocurrency rates and did not study the impact of such a factor as publications in social networks.

Paper [9] analyzes the methods, areas of application, and approaches to analyzing publications and forecasting events based on the collected data, and presents a model for assessing the impact of publications on changes in the cryptocurrency rate, taking into account the posts of only one expert. The author justifies the relevance of the topic and describes the possibilities of appropriate application of the results of the work. The main stages of working with event forecasting data are identified, namely: data pre-processing, further analysis and forecasting. This paper did not study the level of influence of publications of a group of experts in social networks on the cryptocurrency rate.

Paper [10] presents an algorithm for assessing the impact of the publications of a "main expert" on the cryptocurrency rate. This paper describes the process of determining the most influential ("main") expert and obtaining forecasts based on his or her posts on the rate of the selected cryptocurrency. This paper did not investigate the level of influence of all selected experts' publications on social media on the cryptocurrency rate. However, this algorithm is a transitional stage to algorithms for predicting the cryptocurrency rate taking into account the posts of each of the selected group of experts.

As part of the research presented in papers [8–10], appropriate information systems were created to implement the above tasks of data mining.

The above analysis shows that the influence of certain factors on the cryptocurrency rate, in particular the influence of posts by famous people in social networks, is still not sufficiently developed and requires further research.

3. Aim and objectives of the study

The aim of the study is to develop an algorithm for studying the level of influence of posts of each of the selected group of experts in social networks on the cryptocurrency rate.

This algorithm will potentially provide an opportunity to increase the reliability of the forecast regarding the rate of the selected cryptocurrency for the purpose of further formulating recommendations.

To achieve this aim, the following tasks were set:

– to select a group of experts;

– to rank the selected group of experts according to the level of influence on the rate of the specified cryptocurrency;

– to obtain a forecast for the rate of a certain cryptocurrency, taking into account the posts in a certain social network of the selected group of experts based on the previously conducted ranking of experts;

– to formulate recommendations for financial transactions with cryptocurrencies based on the obtained forecasts.

4. 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 experts were 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.

Approximate samples of the datasets are shown in Table 1 and Table 2.

Table 1. *The rate of the selected cryptocurrency for the specified period of time*

A moment in time	Rate value
…	…
t_1	x_1
t_2	x_2
...	...
t_s	x_s
…	…

Table 2. *Number of posts by selected experts for the specified period of time*

Expert	Number of posts	Number of posts related to cryptocurrency
Expert 1	m_1	k_1
Expert 2	m_2	k_2
…		
Expert n	m_n	k_n

Table 1 shows the rates of the selected cryptocurrency x_1, x_2,..., x_s in the selected time period t_1, t_2,..., t_s, which can be taken from the Binance crypto exchange website [11].

In Table 2, m_1, m_2,..., m_n are the frequencies of expert posts, k_1, k_2,..., k_n are the frequencies of expert posts related to a particular cryptocurrency.

The data generated in this way is the input for this study. In the future, it is necessary to:

– analyze the number of posts by selected experts on the social network;

– to rank the group of experts;

– to obtain a forecast of the cryptocurrency rate, taking into account the posts of the selected group of experts after their ranking;

– formulate recommendations for financial transactions in relation to the selected cryptocurrency.

The use of a mathematical apparatus based on the full probability and Bayesian formulas makes it possible to use this information to rank the selected group of experts, depending on the probability with which each expert will post on a social network during the period under consideration [10].

Forecasting the rates of the selected cryptocurrency is carried out using the ATAPSN algorithm [9] (an algorithm based on posts in social networks). To control the accuracy of forecasts, the average relative error is calculated.

Recommendations for financial transactions with cryptocurrencies are formed by entering a critical rate value and calculating the arithmetic mean of cryptocurrency rates for a specified period of time.

5. An algorithm for predicting cryptocurrency rates based on posts of a group of experts in social networks

5.1. Selection of a group of experts

Problem statement:

From the set of users of a social network, we select a subset $A = (a_1, a_2,..., a_n)$ of users who satisfy the following requirements [12]

– the user must be a public figure;

– each user must be active in the selected social network and have a significant number of subscribers;

– users have different professional activities;

– the main professional activity of the users is somehow related to the use of cryptocurrency;

– each pair of users a_i and a_j, $i, j = 1, 2,...n$, $i \neq j$, does not maintain communication in the selected social network (they are not friends and do not respond to each other's posts);

– each user has a sufficient qualification level in the financial sector.

Let's call these users experts. In the future, we will take their posts in the selected social network into account when predicting the rate of a certain cryptocurrency.

Let's assume 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. Expert a_1 published m_1 posts during the specified period of time, 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, etc. The last expert a_n has published m_n posts, of which k_n posts are related to a certain cryptocurrency. Then:

$$m_1 + m_2 +... + m_n = m.$$
$$k_1 + k_2 +... + k_n = k, \tag{1}$$

where m_1, m_2,..., m_n – frequency of expert posts;

k_1, k_2,..., k_n – the frequency of expert posts related to a particular cryptocurrency.

It is necessary to calculate the frequency of posts of all selected experts for an optional time interval [13].

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Justification:

Such a choice of experts is due to the need to form a 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.

5.2. Ranking of a group of experts by the level of influence on the rate of the selected cryptocurrency

Problem statement:

Based on the list of experts: $A = (a_1, a_2, ..., a_n)$ obtained in paragraph 5.1. and taking into account the frequencies of their posts in the selected social network for the specified period of time – $m_1, m_2, ..., m_n$ (also $k_1, k_2, ..., k_n$), given in Table 2, it is necessary to rank the experts in terms of their influence on the rate of the selected cryptocurrency.

The formulated problem can be easily interpreted as a classical probabilistic problem: for a certain period of time, m posts were written. It is known that n experts published posts during this period, where $m_1, m_2, ..., m_n$ are the frequencies of expert posts, $k_1, k_2, ..., k_n$ are the frequencies of expert posts related to the selected cryptocurrency. Event A means that in an arbitrary period of time one of the experts wrote a post related to the selected cryptocurrency. It is necessary to determine which expert is more likely to have made this post [14].

Justification:

Event A – at any moment of time t from the interval $[0; T]$ (in the table 1 $t_1 = 0$, $t_s = T$) a post related to the chosen cryptocurrency was written.

Hypothesis H_1 – the post was written by an expert 1,

hypothesis H_2 – the post was written by an expert 2,

…

hypothesis H_n – the post was written by an expert n.

Let us assume that events H_i and H_j, $i, j = 1, 2, ..., n$, $i \neq j$ are pairwise independent. These assumptions can be made on the basis of the list of requirements that experts must meet (see Section 5.1).

According to the full probability formula:

$$P(A) = \sum_{i=1}^{n} P(H_i) P(A / H_i) \qquad (2)$$

where

$$P(H_i) = m_i / m, \quad P(A/H_i) = k_i / m_i, \qquad (3)$$

m_i – number of publications made by the i-th expert;

k_i – the number of publications made by the i-th expert related to the selected cryptocurrency;

m – total number of publications for the period $[0; T]$;

$P(H_i)$ – the probability that the post was published by the i-th expert;

$P(A/H_i)$ – is the probability that a post related to the selected cryptocurrency was written at any time, provided that this post was written by the i-th expert.

Then, using the Bayesian formula: for each expert, we calculate the probability that the i-th expert created the post, if it is known that it was definitely written by one of the experts during the period under consideration.

$$P(H_i / A) = \frac{P(H_i) P(A/H_i)}{P(A)}, \qquad (4)$$

where $P(H_i)$ – the probability that the post was published by the i-th expert;

$P(A/H_i)$ – is the probability that at any time t from the interval $[0; T]$ a post related to the selected cryptocurrency was written, provided that the publication was written by the i-th expert, $P(H_i / A)$ – is the probability that the post was written by the i-th expert, provided that we know that at any time t a post related to the selected cryptocurrency was created.

The obtained a posteriori probabilities are arranged in descending order. This means that the expert with the highest probability $P(H_i / A)$ will have the greatest impact on the rate of the selected cryptocurrency in the interval $[0; T]$. Next, the expert with the next highest probability $P(H_i / A)$ is selected, and so on. As a result, we get a ranked list of experts according to the impact of their posts on social media on the cryptocurrency rate $A^* = (a_1^*, a_2^*, ..., a_n^*)$.

It should be noted that such a ranking also allows you to assess the impact of a group of experts on the rate of a particular cryptocurrency over the forecast period $[T; T + \Delta t]$, since the impact of publications made during the time period $[0; T]$ also extends to a certain period of time $[T; T + \Delta t]$.

In addition to the above, the following ranking criteria can also be used [15]:

– the number of subscribers is directly proportional to the value of the influence of this expert on a certain audience;

– activity – frequency and regularity of publications on the topic of cryptocurrencies;

– forecast history – the percentage of successful forecasts;

– social capital – cooperation with financial organizations;

– regional influence – influence in a specific geographical region;

– thematic socialization – focus on specific cryptocurrencies or blockchain technologies;

– time factor – the relevance of information and the speed of its dissemination.

It should be noted that the use of each of these alternative criteria for ranking experts requires the use of a unique mathematical apparatus and is planned for further research.

5.3. Obtaining a forecast of the cryptocurrency rate, taking into account the posts in the social network of the selected group of experts based on the ranking of experts

Problem statement:

Let there be some training set $X = (x_1, x_2, ..., x_s)$, where s – is the sample size, which consists of the actual rate of a certain cryptocurrency for the time period $[0;T]$ (the sample is based on the time series from Table 1). It is necessary to obtain forecasts of the rate of the selected cryptocurrency for the next period of time $[T;T+\Delta t]$, taking into account the ranking of experts carried out in paragraph 5.2.

Justification:

The proposed algorithm is based on the following principle: each selected expert has a certain influence on the cryptocurrency rate. In other words, in order to obtain a forecast with the desired accuracy, it is necessary to gradually take into account the posts of not only the "main" (most influential) expert, but also others [10].

Thus, taking into account the posts of each expert from the most influential to the least influential is an iterative process consisting of the following steps:

Step 0. Set a threshold for the mean relative prediction error, as well as the values of T and Δt.

Stage 1

Step 1.1. Using the ATAPSN [9], using the training sample X, obtain forecasts of cryptocurrency rates for the period $[T;T+\Delta t]$, taking into account the posts of the expert who is the first in the ranked list.

Step 1.2. Form a sample X from the time series shown in Table 1 for the time period $[T;T+\Delta t]$.

Step 1.3. From the forecasts obtained in step 1.1 for the time period $[T;T+\Delta t]$, form a sample Y.

Step 1.4. To check the accuracy of the forecast, calculate the average relative forecasting error:

$$MAPE_l = \frac{1}{s}\sum_{l=1}^{s}\frac{|x_l - y_l|}{x_l}100\% , \qquad (5)$$

where x_l – elements of the sample X,

y_l – elements of the sample Y,

$l = \overline{1;s}$, s – the volume of samples X and Y [16].

Step 1.5. If the $MAPE_l$ value does not exceed the specified threshold, the algorithm is complete. If the $MAPE_l$ value exceeds the specified threshold, then proceed to the next step.

Stage 2

Step 2.1. Using the ATAPSN [9], using the training sample X and the forecasts from step 1.1, obtain forecasts of cryptocurrency rates for the period $[T+\Delta t;T+2\Delta t]$, taking into account the posts of the expert who is second in the ranked list.

Step 2.2. Form a sample X from Table 1 for the time period $[T+\Delta t;T+2\Delta t]$.

Step 2.3. From the forecasts obtained in step 2.1 for the time period $[T+\Delta t;T+2\Delta t]$, form a sample Y.

Step 2.4. To verify the accuracy of the forecast, calculate the $MAPE_l$ using formula (5).

Step 2.5. If the $MAPE_l$ value does not exceed the specified threshold, the algorithm is complete. If the $MAPE_l$ value exceeds the specified threshold, then proceed to the next step.

...

Stage n

Step n.1. Using the ATAPSN [9], using the training sample X and the forecasts from step $n-1.1$, obtain forecasts of cryptocurrency rates for the period $[T+(n-1)\Delta t;T+n\Delta t]$, taking into account the posts of the expert who is next in the ranked list.

Step n.2. Form a sample X from Table 1 for the time period $[T+(n-1)\Delta t;T+n\Delta t]$.

Step n.3. From the forecasts obtained in step n.1 for the time period $\left[T+(n-1)\Delta t;T+n\Delta t\right]$, form the sample Y.

Step n.4. To check the accuracy of the forecast, calculate the $MAPE_l$ using formula (5).

Thus, the maximum possible number of steps of the algorithm after receiving forecasts of cryptocurrency rates for the period $\left[T+(n-1)\Delta t;T+n\Delta t\right]$, taking into account the posts of the expert who is the last in the ranked list and calculating the corresponding $MAPE_l$, is n.

It should also be noted that at each stage, the sample X is formed at the corresponding time interval based on the time series from Table 1, and the sample Y is built from the forecasts of the cryptocurrency rate at the same time interval at the same time points as the corresponding sample X. This makes it possible to justify the legitimacy of the transition from time series to statistical samples and thus correctly calculate all MAPEs.

5.4. Formation of recommendations for financial transactions regarding cryptocurrencies based on the obtained forecasts

Problem statement:

Based on the forecast of the rates of the selected cryptocurrency obtained in clause 5.3, formulate recommendations for possible further financial transactions in relation to this cryptocurrency.

Justification:

Obtaining sufficiently accurate forecasts of the rates of the selected cryptocurrency (see paragraph 5.3) allows you to track the trends of their change over the period $\left[T+(n-1)\Delta t;T+n\Delta t\right]$. Based on this, it is possible to make recommendations on the expediency of buying or selling cryptocurrencies in order to make a profit.

It should be noted that when making recommendations, it is necessary to take into account the needs of users. To do this, it is necessary to set a critical value

$$y_{cr}=\begin{cases} y_{am} \geq \mathrm{y_{cr}} \Rightarrow cryptocurrency\,should\,be\,sold; \\ y_{am} < \mathrm{y_{cr}} \Rightarrow cryptocurrency\,should\,be\,bought, \end{cases} \quad (6)$$

where y_{am} – is the arithmetic mean of the sample Y, calculated by the formula:

$$y_{am}=\frac{\sum_{l=1}^{s}y_l}{s}, \quad (7)$$

y_l – sample elements, $l=\overline{1;s}$, s – sample volume.

The value of y_{cr} can be set at the discretion of the user or, based on the opinion of an expert, according to the situation on the cryptocurrency market.

6. Conclusions

This paper presents a modification of the ATAPSN algorithm [9] and expands the list of requirements for selecting experts [12].

The proposed algorithm makes it possible to take into account the level of influence of each expert from the selected group. At the same time, the use of ATAPSN [9] at each stage of the algorithm can significantly simplify the process of obtaining forecasts.

This approach makes it possible to increase the accuracy of forecasts of the rates of the selected cryptocurrency by taking into account the contributions of each of the selected experts, in contrast to the algorithms presented in [9] and [10], in which either a single expert was selected or the "main" expert was determined from the group of experts. That is, in both cases, the potential influence of other experts was neglected.

The proposed algorithm is iterative. At each stage, the posts of one expert were taken into account in the order of the ranked list. That is, at each stage, the previous forecast is refined in case of an unsatisfactory error.

The number of stages of the algorithm, depending on the value of the $MAPE_l$, can vary from 1 to n. This depends on the number of experts whose posts need to be taken into account to achieve the required forecast accuracy.

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 rank the experts.

It should be noted that for different time intervals, different expert ranking results can be obtained.

To use this approach, it is recommended to consider small time intervals (up to a week), each of which can be used to rank experts more accurately. This should potentially increase the accuracy of forecasts of the selected cryptocurrency rates in the specified time interval.

Using the frequency of posts in social media as a parameter for determining the influence of experts allows us to apply the classical apparatus

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of probability theory, which guarantees the correctness of the results obtained.

The obtained forecasts are used to generate recommendations for buying or selling the selected cryptocurrency, depending on the user's needs and the situation on the cryptocurrency market.

The disadvantages include the fact that the accuracy of the forecast may be negatively affected by an unsuccessfully chosen time interval for which the forecast is made, since determining the duration of the impact of a particular expert's forecast is beyond the scope of the task at hand.

Also, the quality of the forecast depends on the selected group of experts, as a poorly selected expert group can negatively affect the algorithm's performance.

These features indicate the need for constant monitoring of both cryptocurrency rates and expert posts on social media.

In order to further improve the accuracy of cryptocurrency rate forecasts and the relevance of recommendations for buying or selling it, it is planned to improve the obtained algorithm by using alternative criteria for ranking experts [15], developing alternative algorithms and incorporating them into the general information technology for determining the impact of social media posts on cryptocurrency rates.

References

1. Preethi, P., Uma, V., Kumar. A. (2015), "Temporal Sentiment Analysis and Causal Rules Extraction from Tweets for Event Prediction", *Procedia Computer Science*. №48. P. 84–89. DOI: https://doi.org/10.1016/j.procs.2015.04.154

2. Gerber, Matthew S. (2014), "Predicting crime using Twitter and kernel density estimation". *Decision Support Systems*. №61. P. 115–125. DOI: https://doi.org/10.1016/j.dss.2014.02.003

3. Alhajj, R., Rokne, J., (eds). (2018), "Encyclopedia of Social Network Analysis and Mining", *Analysis and Mining*. Springer, New York, NY. P. 2699. DOI: https://doi.org/10.1007/978-1-4614-7163-9

4. Culotta, A., Huberman, B. "Towards detecting influenza epidemics by analyzing Twitter messages", Proceedings of the First Workshop on Social Media Analytics. ACM. P. 115–122. 2010. URL: http://snap.stanford.edu/soma2010/papers/soma2010_16.pdf (accessed: 13.10.2023).

5. Chau, M., Xu, J. (2007), "Mining communities and their relationships in blogs: A study of online hate groups", *Int. J. Hum.-Comput. Stud.* 65(1). P. 57–70. DOI: https://doi.org/10.1016/j.ijhcs.2006.08.009

6. Karahoca, D., Karahoca, A., Yavuz, Ö. (2013), "An early warning system approach for the identification of currency crises with data mining techniques", *Neural Comput & Applic*. Volume 23. P. 2471–2479. DOI: https://doi.org/10.1007/s00521-012-1206-9

7. Žukovič, M. (2012), "Dynamics of episodic transient correlations in currency exchange rate returns and their predictability". *centr.eur.j.phys.* Volume 10. P. 615–624. DOI: https://doi.org/10.2478/s11534-011-0120-6

8. Gavrilenko, O., Novakivska, K., Shumeiko, O. (2022), "Select the most influx economic factors for forecasting the US dollar exchange rate", *Bulletin of NTU*. No. 54. P. 26–35. DOI: https://doi.org/10.33744/2308-6645-2022-4-54-026-035.

9. Gavrylenko, O., Miahkyi, M., Zhurakovskyi, Y. (2022), "The task of analyzing publications to build a forecast for changes in cryptocurrency rates", *Adaptive automatic control systems.* Volume 2. No. 41. P. 90–99. DOI: https://doi.org/10.20535/1560-8956.41.2022.271349

10. Bidyuk, P., Gavrilenko, O., Myagkyi, M. (2023), "The algorithm for predicting the cryptocurrency rate taking into account the influence of posts of a group of famous people in social networks", *System research and information technologies: an international scientific and technical journal*. № 2. P. 22–34. DOI: https://doi.org/10.20535/SRIT.2308-8893.2023.2.02

11. Binance cryptocurrency exchange. URL: https://www.binance.com/en/strategy/spot/grid/DOGEUSDT. (accessed: 13.10.2023).

12. Gavrilenko, O., Myagky, M. (2023), "Information system for analyzing the influx of publications of experts on the course of cryptocurrency exchanges based on the rich-agent approach"*, IV International Conference "Software Security Engineering and Advanced Information Technologies" (SoftTech-2023)"*. P. 67–70. URL: https://ela.kpi.ua/handle/123456789/59988 (accessed: 13.10.2023).

13. Kartashov, M. "Internationality, processes, statistics, Publishing and printing center". Kiev University, Kiev, 2008. 504 p. URL: https://probability.knu.ua/userfiles/kmv/VPS_Pv.pdf (accessed: 13.10.2023).

14. Denisyuk, V., Bobkov, V., Pogrebetska, T., Repeta, V. "Higher mathematics. Part 4. The theory of probabilities and mathematical statistics", Edition "NAU-druk", Kiev, 2009. 256 p. URL: https://studfile.net/preview/5797767/ (accessed: 13.10.2023).

15. Gavrilenko O., Myagkyi M. "Study of the influence of the expert group's posts on the course of cryptocurrencies", *XIX International Scientific Conference named after academician Mykhailo Kravchuk Abstracts of reports*.2023. P. 162–164. URL: https://matan.kpi.ua/media/2023/kravchuk-conf-2023/kravchuk2023-abstracts.pdf (accessed: 13.10.2023).

16. Time series. URL: https://kstat.pnu.edu.ua/wp-content/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: 13.10.2023).

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ПРОГНОЗУВАННЯ КУРСУ КРИПТОВАЛЮТИ НА ОСНОВІ РАНЖУВАННЯ ЕКСПЕРТНИХ ОЦІНОК

На сьогодні більшість криптовалютних бірж не мають інструментів, що дали б змогу перевірити й дослідити інформацію, поширену в соціальних мережах щодо тієї чи іншої криптовалюти. Це допомагає організовувати відповідне дослідження з подальшим розробленням необхідного інструменту, що за умови коректного застосування надаватиме користувачам рекомендаційні поради про подальші дії щодо досліджуваної в системі криптовалюти. Ґрунтуючись на цих порадах, зацікавлені особи зможуть коригувати свої рішення щодо подальших фінансових кроків. В основі загальної більшості рекомендаційних систем завжди лежить необхідність установлення деяких факторів впливу, яким пізніше надаються певні вагові коефіцієнти для сприяння та спрощення формулювання подальших порад для користувачів. У цій роботі розглядається саме вплив публікацій відомих осіб на формування цін за певну криптовалюту в конкретний момент часу. Важливість і наявність зазначеного впливу доведено раніше з допомогою статистичних методів. **Мета дослідження** – розроблення алгоритму для вивчення рівня впливу дописів кожного експерта з обраної групи в соціальних мережах на курс криптовалюти. **Об'єктом роботи** є прогноз курсу криптовалют. Як вхідні показники застосовувалися перелік експертів, рівень впливу яких вивчатиметься; інтервал часу дослідження; кількість дописів, що зробив кожен із розглянутих експертів за вказаний період часу; реальні курси криптовалют за відповідний період. Експерти обиралися з-поміж відомих особистостей, які обізнані в галузі фінансів загалом і криптовалют зокрема, або діяльність яких так чи так пов'язана з певною криптовалютою. **Методи дослідження.** Ранжування експертів проводиться на основі формул повної ймовірності та Баєса. Курси криптовалюти за обраний період часу прогнозуються за допомогою певного алгоритму, зважаючи на дописи експертів у соціальних мережах (ATAPSN). Для контролю точності прогнозів обчислюється відносна середня похибка. Рекомендації щодо фінансових операцій із криптовалютою формуються способом уведення критичного значення курсу та обчислення середнього арифметичного курсів криптовалюти за вказаний період часу. **Здобуті результати.** Унаслідок досліджень було розроблено алгоритм, що дає змогу брати до уваги вплив дописів кожного експерта з обраної ранжованої групи на зміни курсів певної криптовалюти. На основі отриманих прогнозів у роботі подана методика формування рекомендацій щодо фінансових операцій з ними.

Ключові слова: курс криптовалюти; алгоритм прогнозування; дописи в соціальних мережах; ранжування групи експертів; інформаційна технологія інтелектуального аналізу.