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FORECASTING THE VOLUME OF RESIDENTIAL REAL ESTATE SALES IN A NEURAL NETWORK BASIS

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While developing the economic part of a construction project, a cash flow model is built to consider all the key factors that affect the overall project management system. An important component in building a cash flow model is knowing the volume of future sales. Forecasting the volume of sales allows you to predict the income from the implementation of the project and assess its profitability. Currently, construction companies assess volume of sales expertly, and the results of the forecast depend on the expert's experience. In order to improve the efficiency of building a cash flow model, the paper pro-poses a neural network (NN) model for forecasting of the volume of real estate sales considering market factors. The model is built on the basis of the Loginom analytics platform, trained and has good predictive properties. The average relative forecast error is 5.21%. The model considers statistically significant external and internal factors affecting the volume of real estate sales under shared-equity construction in the Chelyabinsk region market.

Keywords: cash flow model; Loginom analytics platform; machine learning; artificial intelligence; data analysis; neural network forecasting.

Introduction

When developing the economic part of a construction project, it is extremely important to control cash flow, as it helps to avoid financial risks and achieve positive results. In this regard, a cash flow model is built, in which all the key factors affecting the overall project management system should be considered. The purpose of building a cash flow model is to assess the ability of an enterprise to generate cash in the required amounts and within the timeframe required for planned expenses. In addition, this model will help to evaluate the project efficiency, calculate revenue, profit/loss.

Cash flow management is one of the key components of comprehensive project management, and building a cash flow model is a prerequisite for achieving successful results. The purpose of building a cash flow model is to assess the ability of an enterprise to generate cash in the required amounts and within the timeframe required for planned expenses. In addition, this model will help to evaluate the project efficiency, calculate revenue, profit/loss.

Housing construction is often carried out with the attraction the funds of equity construction investor under a contract of participation in shared construction.

In accordance with the Federal Law No. 214-FZ (on participation in shared construction), from July 1, 2019, escrow accounts must necessarily be used for payment under the contract of participation in shared construction. The money of shared construction investors is not transferred to the company's account, but is frozen in a special bank account, which is disclosed after the house is delivered.

The following problems arise due to this change:

1) The company has to build with loan money borrowed from the bank.

2) The loan interest rate depends on the balance of the escrow accounts. And this amount is determined by the number of real estate sales in a new building, the size of which is unknown in advance when planning and at the beginning of construction.

3) The company's profit depends on revenue, which is determined by the balance of escrow accounts, i.e. on the number of future real estate sales.

4) Until the housing is delivered, the company does not make any profit.

Currently, regional construction companies use expert subjective assessment of future sales volumes. Expert forecasting requires in-depth analysis of both quantitative and qualitative factors. The method requires a lot of experience of experts and is not formalized. Therefore, the planned financial indicators are inaccurate and largely indicative [1,2].

Consequently, the forecasting the volume of real estate sales by a regional construction company based on methods of analyzing retrospective sales data is relevant [3-8].

Analytical and information forecasting methods have been developed. Economic and mathematical models designed to solve the forecasting problem have the following disadvantages:

1) When analytical methods are used, an existing formal model that describes the original object is selected. However, the resulting model is abstract and greatly simplifies economic processes.

2) Statistical analytical methods consist of building a regression model based on historical information of sales volume values. The methods assume the possible course of the simulated process, which leads to significant modeling errors.

3) Each construction company develops forecasting models based on its experience.

Therefore, the models are not universal and generally cannot be applied to obtain the forecast values of another company.

1. Research Methods

Business processes are poorly formalized; therefore, information models are used for their analysis, the parameters of which are determined in the process of their training based on accumulated retrospective data. This allows considering all the features of real processes.

When building a model for forecasting the volume of real estate sales in new buildings at the level of a separate regional company, the following provisions were considered.

1. An information approach should be used to build a procedure for fore-casting sales volume by a regional company.

2. The machine learning model allows you to consider many external and internal factors (economic, social and political) that can affect the results of the forecast.

3. Data mining methods based on neural network training are currently used to build prediction model based on machine learning.

Advantages of the neural network [9-19] training:

- Nonlinearity of the model, which allows to display any nonlinear functions.

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• Locality of perception, which consists in the fact that each neuron perceives not the entire input vector, but only one of its coordinates. Localization of perception, which is that each neuron does not perceive the entire input vector, but only one of its coordinates.

• During the training process, it is possible to configure the NN architecture. This allows the NN to perceive abstract features.

• It learns well based on a combination of different characteristics.

4. The neural network training requires a large sample of retrospective training examples, which must meet the CRISP-DM data analysis standard.

An important step in building a model is the selection of indicators that will be used for modeling. The availability of information is of great importance. The selected indicators should be presented quantitatively in official government statistics.

Many factors influence the decision to buy an apartment. Individual factors influencing the decision to purchase residential real estate are of great importance. Buyers usually evaluate the location of the property; the development of social institutions: kindergartens, schools, shops; accessibility of transport; prestige of the construction company and many others. However, such information is usually inaccessible to the researcher, and it is impossible to quantify it.

The hypothesis of the study is the assumption that 3 groups of factors should be used to obtain good predictive properties of the model:

1) Indicators characterizing a buyer: financial capabilities (per capita income, average monthly salary), the number of mortgage housing loans, the number of family loans spent on improving housing conditions. The indicators are conventionally called regional, as they are determined at the level of a particular region.

2) Internal retrospective data is a time series of real estate sales for an already completed project and the cost of 1 sq. m. of living space. This data is uploaded from the corporate information system.

3) Indicators that are determined at the federal level: % of inflation in the country and the annual interest rate of the Central Bank.

The choice of retrospective data is significantly influenced by the technical and economic characteristics of the project [20].

According to the outlined provisions, three groups of factors are applied to the input of the neural network. The output is the forecast value of the volume of real estate sales (Fig. 1).

Components of the input vector X:

$x_1, x_2, \ldots, x_k$ are corresponded to regional data,

$x_{k+1}, x_{k+2}, \ldots, x_m$ are variables corresponding to federal factors,

$x_{m+1}, x_{m+2}, \ldots, x_n$ is the time series of sales.

Here n is the size of the input vector, k is the amount of data determined at the regional level, and m is the number of federal factors.

Y is the output forecast value of the volume of real estate sales.

Figure 2 shows the author's process technology of the neural network forecasting of volumes of real estate sales in the primary regional market.

The input of the model is a training set of examples. The set of input parameters X includes three groups of factors: external federal and regional, as well as retrospective sales data. The set D is the known values of sales volumes corresponding to the set X.

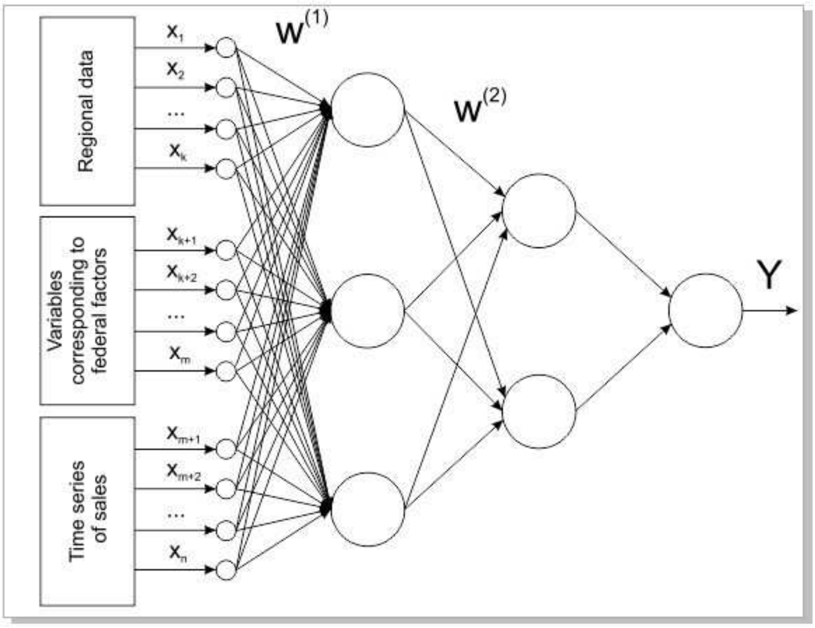

Fig. 1. Conceptual diagram of a neural network

For analysis, structured data is used, i.e. ordered and organized in the form of flat two-dimensional tables and has a certain quality.

In step 2, significant factors were selected based on the Pearson correlation coefficient.

In step 4, the validation method, training parameters and hyperparameters of the network, such as the number of layers and neurons in them, are set up. The number of neurons in the hidden layers and the number of hidden layers is selected so that the number of connections formed by them is less than the number of training examples by at least two or three times.

Three data sets are used for training:

1. Training set is a set of data that is used to train a network.

2. Validation set is a set of data that is used in the learning process to select hyperparameters of the network.

3. Test set is a set of data that is used to evaluate the quality of the network performance after its training is completed.

The sampling method is random. Therefore, all three sets are different and selected independently.

The average relative error is used to assess the quality of neural network training

$$E = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - d_i|}{y_i} \cdot 100\%. \tag{1}$$

where n is the size of the training sample; d_i is the actual value of real estate sales volume; y_i is the forecast value of the real estate sales volume. During the training process, the synaptic weights and hyperparameters of the neural network are adjusted to minimize the error (1). To minimize the error in the neural network training, an iterative Broyden-

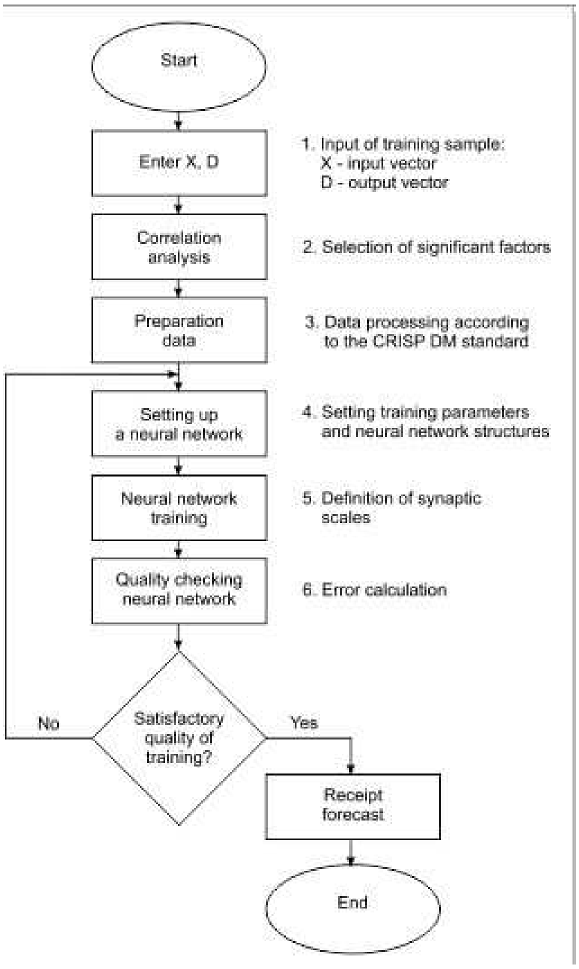

Fig. 2. Sales volume forecasting technology

Fletcher-Goldfarb-Shanno numerical optimization algorithm with limited memory usage (L-BFGS) is used.

2. Results of the Study and Discussion

The low-code Loginom platform (Loginom Company) is used to build a neural network forecasting model [21]. Data preparation was performed according to the CRISP-DM standard.

The proposed concept of neural network forecasting of sales volume in the regional market, implemented on the Loginom platform, has a modular structure (Fig. 3).

The Data preparation module, the Correlation Analysis module and the Sales Forecasting module are universal. The Neural Network Model module is a trained neural network that is configured on the data entered in the Data Preparation module.

Statistical data of the regional real estate sales market of one of the construction companies of the Chelyabinsk region were used for training and testing the model. A regional construction company provided retrospective monthly sales data for the first stage of a project in 2018-2022 which was included into multiple examples to forecast of the second stage of the same project.

The training set also includes statistical indicators published by the Central Bank of

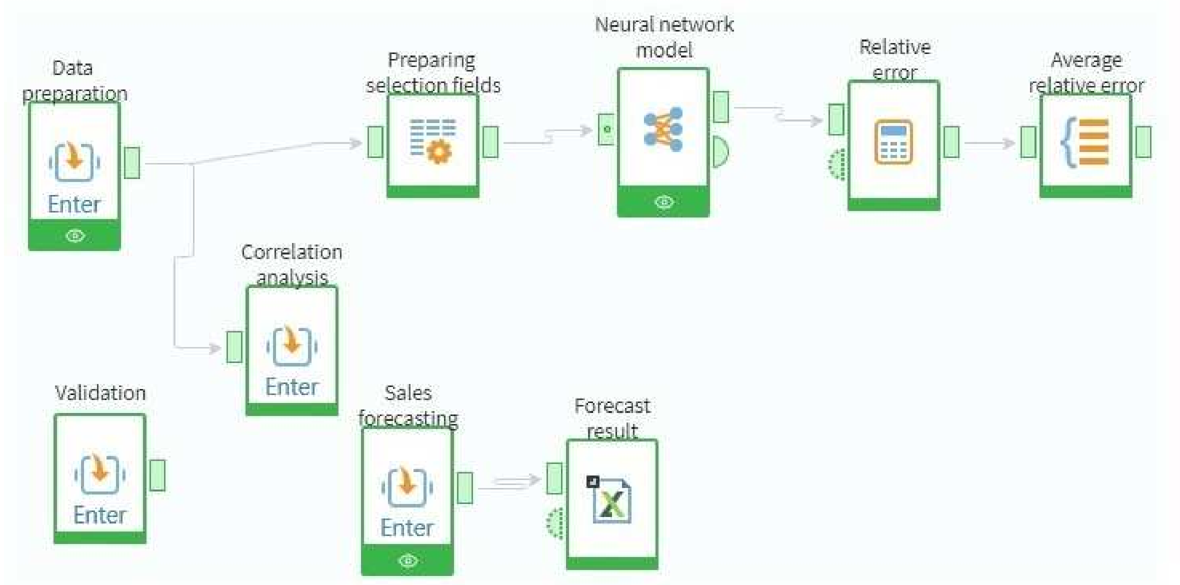

Fig. 3. Implementation of the forecasting model on the Loginom platform

ab Field1.Label	ab Field2.Label	9.0 Pearson
Number of sales	Average price sq.m	0,09
Number of sales	Total revenue	0,90
Number of sales	Number of housing loans	0,64
Number of sales	Number of mortgage housing loans	0,64
Number of sales	Average monthly salary, rub	0,07
Number of sales	Interest rate % per annum	-0,32
Number of sales	% inflation	-0,12
Number of sales	Number of persons, maternity capital	0,39
Number of sales	Average per capita cash income, rub	0,04

Fig. 4. Correlation of the number of sales with the input indicators

the Russian Federation, the Ministry of Finance of the Russian Federation, the Ministry of Economic Development of the Russian Federation, and the Federal State Statistics Service for the Chelyabinsk Region [22-25].

In the Correlation Analysis module, significant input indicators are selected (Fig. 4).

There is a weak negative linear correlation between the number of sales and the size of the annual interest rate and % inflation. This is natural, because both indicators affect the interest rates of banks when taking out loans for the purchase of housing.

There is a weak correlation between the volume of real estate sales and the price per square meter, the per capita income and the average monthly salary of a buyer.

Previously, it was suggested that the financial capabilities of a buyer are influenced by the per capita income and the average monthly salary of a buyer. The study has shown that

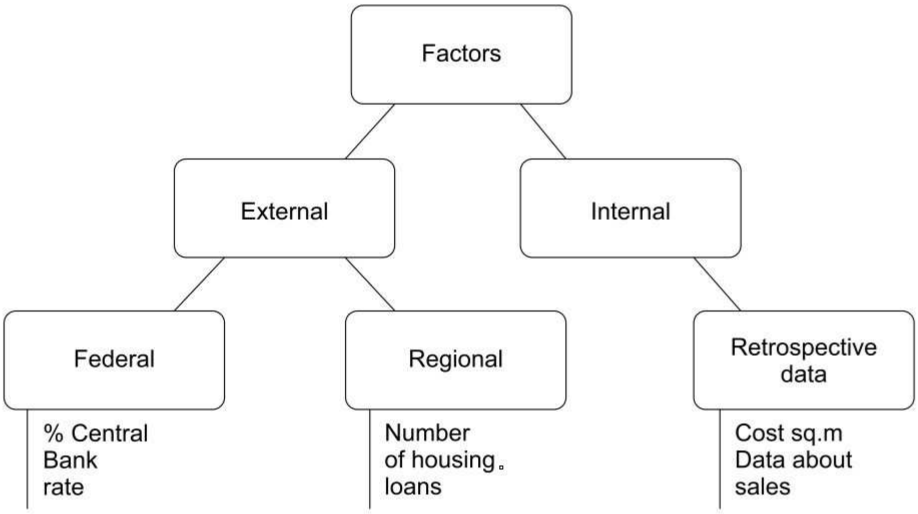

Fig. 5. Factors influencing sales figures

loans have a greater impact on the purchase of real estate. The factors used for training the neural network forecasting model are shown in Fig. 5.

Neural network training is performed in the Neural Network Model module (see Fig. 3) based on real retrospective market data. The neural network has 8 input and 1 output variables (Fig. 6). During network training, a weight matrix is calculated, and the number of hidden neurons is adjusted.

Inputs	Outputs	Name	Data kind	Usage type
12 Year	12 Year	Data_Y_1	Discrete	Input
12 Month	12 Month	Data_M_1	Discrete	Input
12 Number of sales	12 Number of sales	Vyruchka_Count	Continuous	Output
9.0 Average price sq.m	9.0 Average price sq.m	tsena_za_kvadrat	Continuous	Input
9.0 Total revenue	9.0 Total revenue	Vyruchka_Sum	Continuous	Input
12 Number of housing loans	12 Number of housing loans	Kolichestvo_zhilischnykh_kreditov	Continuous	Input
12 Number of mortgage housing loans	12 Number of mortgage housing loans	Kolichestvo__ipotechnykh_zhilischnykh_kre...	Continuous	Input
9.0 Interest rate % per annum	9.0 Interest rate % per annum	Razmer_stavki___godovykh	Continuous	Input
12 Number of persons maternity capital	9.0 Number of persons maternity capital	CHislennost_lits__rasporyadivshikhsya_chas...	Continuous	Input
9.0 % inflation	9.0 % inflation	__inflyatsii	Continuous	Input

Fig. 6. List of neural network input data

Three subsets were selected from the training set: 80% of the training set, 20% of the testing set. The confirmatory analysis was performed using K-fold cross-validation at $k = 10$.

A comparative chart of the actual and forecast values of sales volume is shown in Figure 7.

The average error on the training set is 0.06 (Fig. 8), on the test set is 0.30, on the validation set is 0.34.

The average relative forecast error calculated by the formula (1) is 5.21%.

The developed model allows creating a forecast for three different scenarios of economic development: optimistic, pessimistic and realistic.

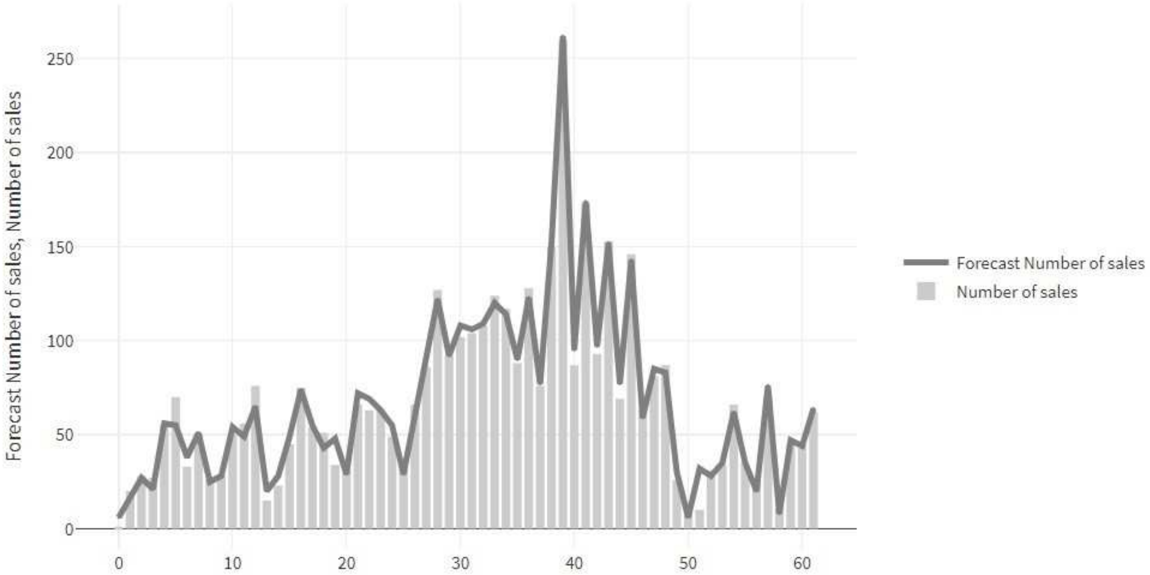

Fig. 7. Sales volume comparison chart

Name	Caption	Value
9.0 TrainRMSError	The root-mean-square error of the training set	14,05
9.0 TrainAvgError	The mean absolute error of the training set	13,31
9.0 TrainAvgRelError	The mean relative error of the training set	0,80
9.0 TestRMSError	Root-mean-square error in the test set	15,64
9.0 TestAvgError	The test set mean absolute error	14,63
9.0 TestAvgRelError	The test set mean relative error	0,98

Fig. 8. Learning errors

1. The optimistic scenario assumes preservation of the current indicators of the real estate market development with stability of the macroeconomic situation.
2. The pessimistic scenario models the deterioration of any macroeconomic indicators.
3. The realistic scenario provides for the preservation of macroeconomic parameters.

The forecast of sales volume by a regional company for 2023 (Fig. 9) was made for an optimistic scenario, i.e. it was assumed that the current trend of real estate market development and stability of macroeconomic indicators, both at the federal and regional levels, would be maintained.

Conclusions

1. The article proposes the concept of neural network scenario forecasting of the real estate sales volume in the primary regional market. The concept considers three groups of factors: external macroeconomic parameters determined at the federal level; external regional parameters and internal retrospective sales data of a construction company.
2. Based on the proposed concept, a neural network model is implemented, which can be used for scenario forecasting of sales volume in the regional primary market of residential real estate.

12 Year	12 Month	12 Forecast
2 023	1	38
2 023	2	56
2 023	3	64
2 023	4	71
2 023	5	66
2 023	6	71
2 023	7	66
2 023	8	63
2 023	9	60
2 023	10	65
2 023	11	64
2 023	12	59

Fig. 9. Forecast results

3. The model was used on real data from a construction company in the Chelyabinsk region.

4. The model considers statistically significant external and internal factors affecting the volume of real estate sales under shared-equity construction in the Chelyabinsk region market.

5. The developed model is universal and allows making a forecast with changing macroeconomic indicators.

The obtained forecast values of real estate sales volumes will be determined by external economic factors, which is of practical importance for any construction company in the conditions of shared construction.

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ПРОГНОЗИРОВАНИЕ ОБЪЕМА ПРОДАЖ ЖИЛОЙ НЕДВИЖИМОСТИ В НЕЙРОСЕТЕВОМ БАЗИСЕ

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При разработке экономической части строительного проекта строится модель движения денежных средств (ДДС), в которой необходимо учесть все ключевые факторы, влияющие на общую систему управления проектом. Важным компонентом в построении модели ДДС является знание объема будущих продаж. Прогнозирование объема продаж позволяет спрогнозировать доходы от реализации проекта и оценить его рентабельность. В настоящее время строительные компании оценивают объем продаж экспертно, причем результаты прогноза зависят от опыта эксперта. С целью повышения эффективности построения модели ДДС в статье предлагается нейросетевая модель прогнозирования объема продаж недвижимости с учетом рыночных факторов. Модель построена на базе аналитической платформы Loginom, обучена и имеет хорошие прогностические свойства. Средняя относительная погрешность прогнозирования 5,21%. Модель учитывает статистически значимые внешние и внутренние факторы, влияющие на объем продаж недвижимости в условиях долевого строительства на рынке Челябинской области.

Ключевые слова: модель движения денежных средств; аналитическая платформа Loginom; машинное обучение; искусственный интеллект; анализ данных; нейросетевое прогнозирование.

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