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# Neural Network Models and Cognitive Computing from Social Media Data: Perception of Situation

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**Abstract**: The paper presents the development of various types of models using cognitive computing based on speech data of social media actors to reveal the presence/absence of social tension in the areas where urban development projects are being implemented, as illustrated by the construction of the Nizhegorodskaya transport interchange hub in Moscow (Russia). The empirical base of the study was data from social networks, microblogs, blogs, instant messengers, video hosting sites, forums, Internet media, subject-related portals and reviews on the project implementation. The research was carried out using a transdisciplinary approach, including semantic analysis, neural network technologies and mathematical modeling methods. The study showed the consistency of the results obtained during the application of various types of models. Semantic analysis of content using neural network technologies showed a neutral perception of the project by residents, the absence of social stress in the construction areas. The results of the analysis performed with autoregressive models confirmed the results obtained.

***Keywords***: social media, neural network technologies, speech perception, natural language processing, time series, differential equations

## 1. INTRODUCTION

Cognitive research has recently attracted more and more attention from researchers. Cognitive computing generalizes various process approaches, such as artificial neural networks, fuzzy systems and evolutionary computing, for modeling human cognitive abilities (thinking, learning, reasoning, etc.) using computer models [1]. Cognitive computing is used in various professional fields: in medical information processing, video analytics, cognitive robotics, predictive analytics, machine learning, applications and many others [2, 3]. Applications of cognitive management and cognitive computing in the fields of risk management, cognitive fraud detection, and in business decision making have shown their effectiveness. For example, by analyzing patterns in big data, small data, and "dark data," cognitive technologies can detect human behavior and suggest options for personalizing of products and services [4]. New algorithms and methods in a variety of fields are presented, together with solution-based approaches. The topics addressed include various theoretical aspects and applications of computer science, artificial intelligence, cybernetics, automation control theory, and software engineering [5]. In the recent era, smart methods with human touch called as human cognition is adopted by many researchers in the field of information technology with the Cognitive Computing [6]. The high demand for cognitive computing in various areas of natural language processing is quite predictable, for example, in text analytics, for building conversational

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interfaces, context based quantum language model with application to question answering, named entity recognition and others [3, 7].

Aim of the study: development of various types of models using cognitive calculations based on speech data of social media actors to reveal the presence/absence of social tension in the areas where urban development projects are being implemented, as illustrated by the example of the construction of the Nizhegorodskaya transport interchange hub (TIH) in Moscow (Russia).

### *1.1. Data*

The empirical base of the study was data from social networks, microblogs, blogs, instant messengers, video hosting, forums, Internet media, subject-related portals and reviews on the implementation of the Nizhegorodskaya TIH project (Fig. 1). Date of collection: January 1, 2020 - March 31, 2021 (Table 1, Fig. 2, 3, 4, 5).

**Table 1.** Quantitative parameters of the data

| *Parameter* | *Value* |
|---|---|
| Number of messages: | 3 999 |
| Maximum number of messages per day: | 533 |
| Number of active actors: | 397 |
| Activity (posts per actor): | 10,07 |
| Number of sources: | 111 |

**Fig. 1.** Nizhegorodskaya TIH

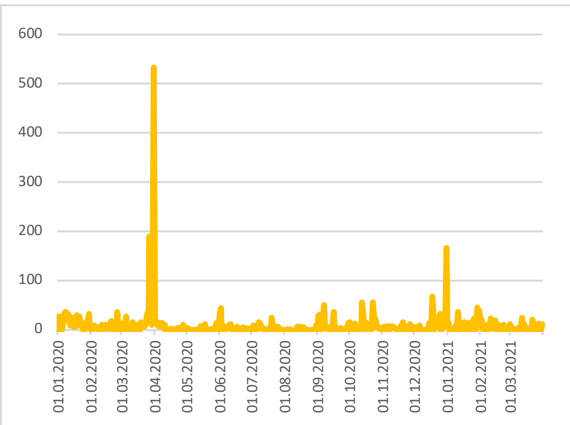


**Fig. 2.** Dynamics of messages

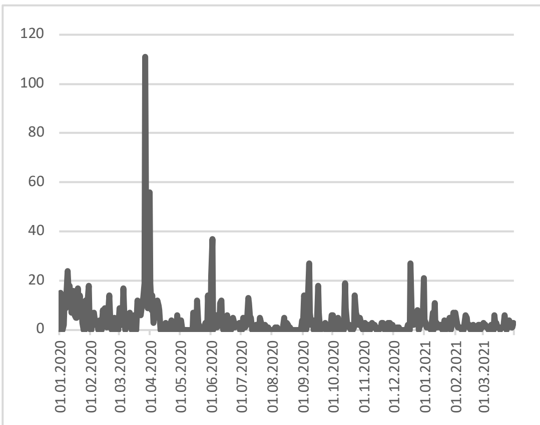


**Fig. 3.** Dynamics of unique messages

 

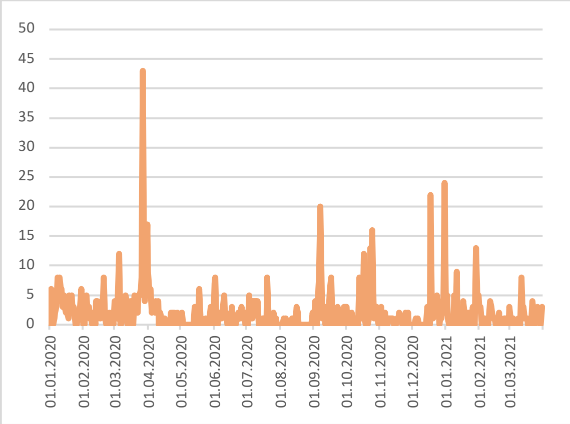


**Fig. 4.** Actors' activity dynamics

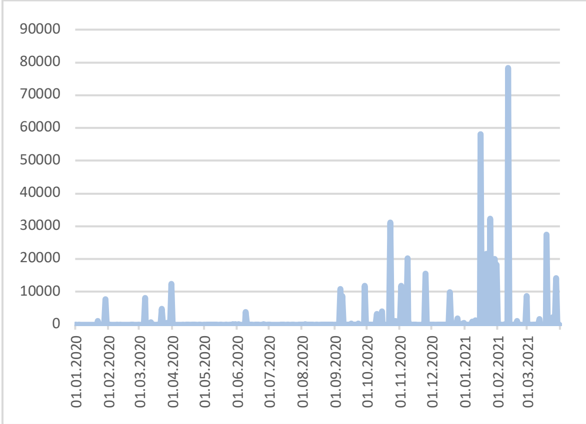


**Fig. 5**. Dynamics of views

The implementation of the Nizhegorodskaya TIH project began a long time ago. The first stage of the Nizhegorodskaya transport interchange hub was started on March 27, 2020 simultaneously with the extension of the Nekrasovskaya subway line and the opening of the Nizhegorodskaya subway station; however, the TIH has not yet started to function as an integral complex. Now the TIH implementation project is in the final stages of commissioning. According to the heads of the Stroykompleks, a distribution hall for TIH and subway users will open in the near future. In the media space, information about the project implementation is presented in a fairly complete manner.

### *1.2. Method*

The data was collected using Brand Analytics algorithms. A transdisciplinary approach was used to interpret the data.

Neural network technology TextAnalyst 2.3 allowed to identify and analyze the topic structure of the database, identify the semantic network and analyze the core of the semantic network, conduct summarization and analysis of word associations. Sentiment analysis was performed using the sentiment determination module, Eureka Engine. Content analysis was performed using the AutoMap service. For visual analytics, the Tableu platform was used.

An important result of data filtering is the creation of data subsets for building mathematical models in order to analyze the situation in detail. When formalizing the problem, the object of study was considered as a dynamic system. To analyze the behavior of a dynamic system, time series models and differential equations are used. Time series models are built using regression models [9,10] and convolutional neural networks [11]. When choosing the general form of the differential equation [12], the problem under consideration is presented as a rivalry problem. When approximating the model coefficients, the Nelder-Mead method was used. The constructed models were studied for structural stability [12].

## 2. RESULTS AND DISCUSSIONS

### *2.1. General description of the content*

Analysis of the data showed that the most significant, key content topics related to the Nizhegorodskaya TIH project were revealed in messages, the dynamics of which had only one peak of activity, that is, on 31.03.2020, with an insignificant quantitative value of 533 and, obviously, were a reaction to the peak of growth in the number of unique messages and the total number of authors observed on 27.03.2020 (Fig. 2, 3, 4). The peak of the growth in the number of unique messages falls on 27.03.2020 with a quantitative value of 111 (Fig. 3). The date 27.03.2020 is also the peak of the growth in the total number of authors with a quantitative value of 43. (Fig. 4). Such activity was caused by the announced opening of the subway station and TIH Nizhegorodskaya (27.03.2020). The peak in the number of views on January 16, 2021 (58 011) was caused by the information that 11 new subway stations will appear in Moscow in 2021. The largest number of views on 11.02.2021 (78 310) followed the message about Anna Merkulova, the head of the main engineering center of Russia (coverage of 11 185), and on 11.02.2021, S. Sobyanin's message about the completion of the Vostochny station construction in Moscow was published.

The most significant content topics related to the construction of the Nizhegorodskaya TIH were generated by actors from various countries. Most of the actors with determined geolocation belonged to Russia, which is natural, but users from Ukraine, Spain, Indonesia and Japan also took part.

Key topics related to the project were generated on various digital platforms. The audience coverage shows that microblogs took the first place; the second and third places in the rating were taken by social networks and blogs, respectively (Fig. 6).

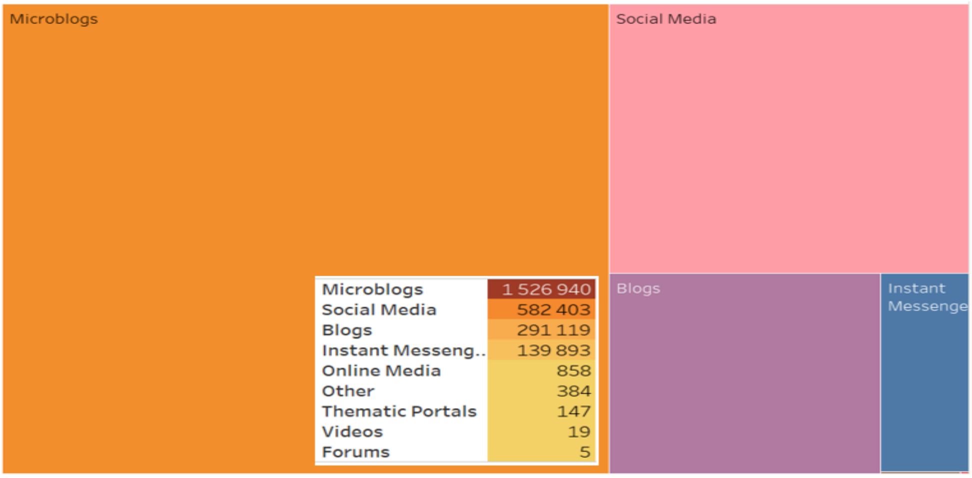


**Fig. 6.** Ranking of types of sources by audience coverage

Meanwhile, analysis of comments, likes, reposts and duplicates showed that social networks were in the lead in the ranking of digital platforms. Actors also left comments and reposts in microblogs and blogs. Likes are predominantly presented on social networks; they are also found in messengers and microblogs. Actors made duplicates of information about the project in social networks, as well as in the Internet media and microblogs (Fig. 7).

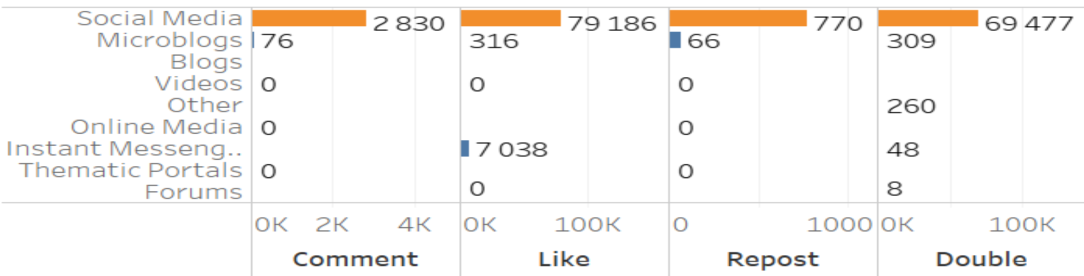


**Fig. 7.** Ranking of types of sources by digital footprints

Thus, passive users received information about the Nizhegorodskaya TIH project from microblogs mainly, and active users preferred social networks, where they actively generated digital footprints that demonstrated a reaction to the Project implementation.

Analysis of sources according to the number of messages shows that key content topics were covered mainly on official resources, and the ranking of digital platforms where the content with the highest ratings was generated is led by Instagram, Facebook, Twitter and VKontakte (Fig. 8).

 

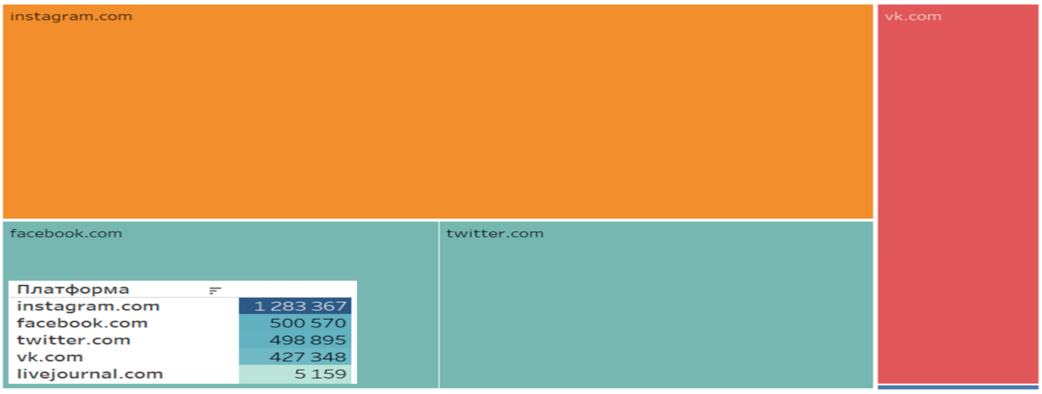


**Fig. 8.** Ranking of digital platforms based on user preferences

## *2.2. Content sentiment*

The analysis of the data made it possible to determine the sentiment of the overwhelming number of messages as neutral (2 404 940). Negative reactions were insignificant (21,234) (Fig. 9).


**Fig. 9.** Content sentiment by coverage

Analysis of the content sentiment by type of source and by coverage shows that the neutral content was generated mainly in microblogs, as well as in social networks and blogs. Most of the positive content was posted on social networks, as well as messengers and blogs. The negative content was presented in blogs; a small amount was also presented in instant messengers and social networks (Fig. 10).

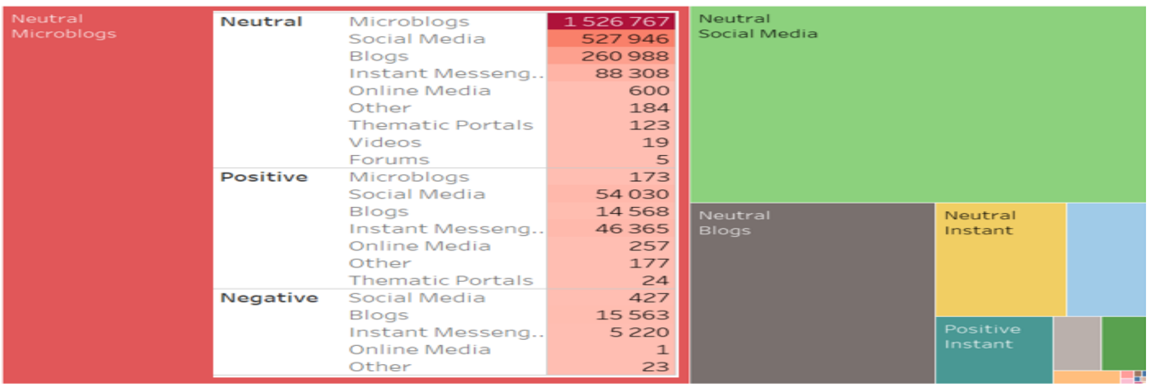


**Fig. 10**. Content sentiment by type of source and coverage

The study of the distribution of actors' digital footprints with various sentiment types by types of sources allowed creating rankings, where the top sources are as follows: in terms of positive sentiment: vk.com, mos.ru, mperspektiva.ru (Fig. 11), in terms of neutral sentiment: vk.com, instagram.com, mos.ru (Fig. 12), and in terms of negative sentiment: gucodd.ru, vk.com, livejournal.com (Fig. 13).

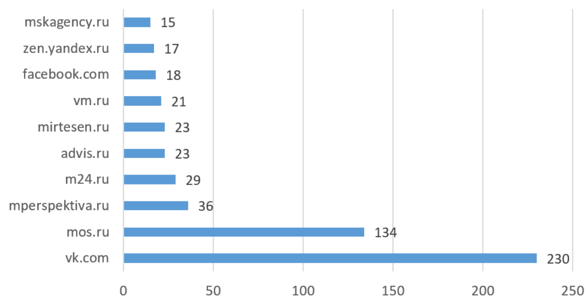


**Fig. 11.** Ranking of sources by positive sentiment

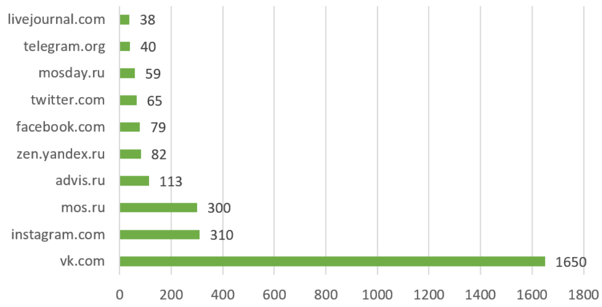


**Fig. 12.** Ranking of sources by neutral sentiment

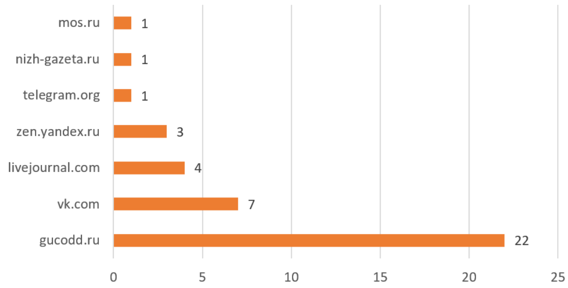


**Fig. 13.** Ranking of sources by negative sentiment

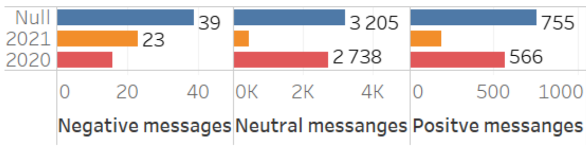


**Fig. 14.** Dynamics of messages with different types of sentiment

In addition, the dynamics of messages with different types of sentiment and the ranking of sources by sentiment demonstrates an increase in negative messages and a decrease in neutral and positive references to the implementation of the Nizhegorodskaya TIH project over the analyzed period (Fig. 14).

### *2.3. Key topics*

To analyze the most important key topics of the content related to the Project, the database was divided into three clusters according to the sentiment types (Table 2).

**Table 2.** Key topics of the clusters with different types of sentiment

| Negative cluster | Positive cluster | Neutral cluster |
|---|---|---|
| • Station renaming.<br>• Information about the financial scheme of the MR Group, which is linked to the future multifunctional center within the Ryazan Terminal 1 TIH (next to the Nizhegorodskaya MCC station).<br>• Design of Nizhegorodskaya station; color scheme of the lobby.<br>• Plan of the areas adjacent to the Nizhegorodskaya TIH, public transport stops.<br>• Traffic restrictions due to road works.<br>• Alleged poor quality of construction, lack of confidence in inspections initiated by the Moscow authorities.<br>• Network actors believe that it was counterproductive to connect the | • Information about the opening of the subway station and Nizhegorodskaya TIH.<br>• The completion schedule for the construction of the eastern section of the subway Big Line by the end of 2022, as announced by the press service of the mayor and the Moscow government.<br>• Announcement of the construction schedule for the Elektrozavodskaya station of the Big Circle Line (BCL).<br>• Information about the TIH features (at grade parking, pedestrian bridge over the Yauza River with a length of 85 meters), which will improve the transport situation, create comfortable aesthetic conditions for residents. | • S. Sobyanin's tweet about the opening of the fifth flagship center @mydocs_mos in the southeast of Moscow in the Gorod shopping center. The MFC of the Nizhny Novgorod region has also moved here. The shopping center is located on Ryazansky Prospekt, next to the TIH, which unites the stations of the BCL, the Nekrasovskaya subway line, the MCC and the railway.<br>• Announcement that 11 new subwat stations will appear in Moscow in 2021.<br>• Information about the construction of the largest TIH in Europe near the Nizhegorodskaya subway station and of a cross-platform transfer hub. |

| | | |
|---|---|---|
| Kommunarskaya and Biryulyovskaya subway lines; the initial decision to connect the Kommunarskaya and Nekrasovka lines seems more logical to them.<br>• The cross-platform nature of the future TIH will lead to increased complexity; passengers will get confused.<br>• The ill-conceived location of the station. It is located far from the stops and near the cemetery, which does not look very good; the station had to be located according to the old routing projects.<br>• Premature opening of stations, three stations were opened too early and they could be opened already as part of the BCL | • Information that the Nizhegorodskaya BCL station will become part of the Ryazanskaya TIH.<br>• Plans to build a multi-tiered landscape park on Ryazansky Prospekt, which will become a buffer zone between residential areas and the Ryazanskaya transport hub.<br>• Information that the new section of the South-Eastern Chord from Ryazansky Prospekt to the Third Transport Ring will improve the transport situation in the South-Eastern Administrative District; in particular, comfortable approaches to the Novokhokhlovskaya and Nizhegorodskaya TIHs will appear.<br>• Information about the details of the subway construction | • Information on the construction schedule for the subway Big Ring.<br>• News about the rating of cheap new buildings near new TIHs.<br>• Announcement of the awarding of Anna Merkulova.<br>• Announcement of plans for the construction of the Ryazanskaya TIH, which will be erected at the intersection of Ryazansky Prospekt with Nizhegorodskaya Street, on the basis of the Nizhegorodskaya subway station.<br>• Information about plans for the TIH and subway construction in the capital.<br>• Information on the schedule for the opening of the passengers lounge in Nizhegorodskaya TIH.<br>• Messages about Moscow mayor's personal control over the construction |

### *2.4. Revealing the presence/absence of social stress in the areas of the Nizhegorodskaya TIH construction*

The result of the database analysis showed the absence of social stress (0.89) and the average social well-being index (8.75) (Fig. 16).

The analysis of the sentiment of actors' digital footprints confirmed the absence of social stress in the areas of the Project implementation and the city of Moscow in general. Only 57 likes and 3 reposts indicated negative reactions (Fig. 23). Meanwhile, 79 062 likes, 2 749 comments and 744 reposts speak for neutral reactions, and positive reactions are expressed in 7 421 likes, 157 comments, 89 reposts (Fig. 15).

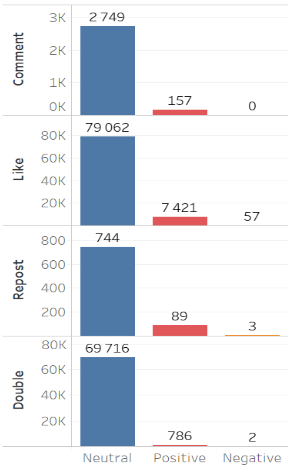


**Fig. 15**. Digital footprint sentiment

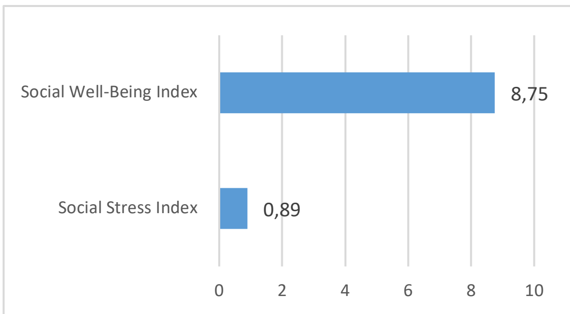


**Fig. 16.** Social Well-Being Index and Social Stress Index

### *2.5. Results of mathematical modeling*

The data obtained as a result of the filtration is time series of the studied dynamic process [13,14]. For time series, we introduce the following notation:

**poz(t)** is the number of messages at time *t* with a positive attitude towards the TIH construction;

**neg(t)** is the number of messages at time *t* with a negative attitude towards the TIH construction;

**ntr(t)** is the number of messages at time *t* with a neutral attitude towards the TIH construction.

*2.5.1. ARMA models*

*Models for time series data with a positive attitude*

After identifying and correcting anomalous points in the time series {*poz(t)*}, a trend can be identified based on the time series data:

$$\widehat{poz}(t) = 0.5 + 0.005t \tag{1}$$

The positive coefficient in front of *t* in (1) indicates that the number of positive messages increases over time. The adequacy of the construction of the model (1) has been verified by various methods. In particular, the hypothesis of the inadequacy of model (1) according to Fisher's criterion was rejected at a significance level of $p = 0.001620$, which indicates a good quality of the constructed model. To construct a model of the random component, we find the remainders of series $E_{poz}(t) = poz(t) - \widehat{poz}(t)$.

For the remainders of series $E_{poz}(t) = poz(t) - \widehat{poz}(t)$, after testing the hypothesis for stationarity, an autoregressive model ARIMA (2,0,2) was constructed.

$\hat{E}_{poz}(t) = -0.1E_{poz}(t-1) - 0.4E_{poz}(t-2) - 0.24\varepsilon(t) + 0.2\varepsilon(t-1)$,

where $\varepsilon(t) \in N(0; 4.4)$

*Models for time series data with a negative attitude*

Models for time series {*neg(t)*} were constructed using an algorithm similar to.

After correcting anomalous points, a trend can be identified according to the time series {*neg(t)*} data:

$$\widehat{neg}(t) = 0.02 + 0.0001t \tag{2}$$

The positive coefficient in front of *t* in (2) indicates an increase in the number of negative messages, but the rate of growth in the number of negative messages is much less than the growth in the number of positive messages. The model was checked for adequacy. In particular, the hypothesis of the inadequacy of model (2) according to Fisher's criterion was rejected at a significance level of $p = 0.14$, which indicates a satisfactory quality of the constructed model. To construct a model of the random component, we find the remainders of series $E_{neg}(t) = neg(t) - \widehat{neg}(t)$.

*For the remainders of the series, an ARIMA (5,0,5) model was constructed.*

$$\hat{E}_{neg}(t) = -0.4E_{neg}(t-4) - 0.4E_{neg}(t-5) + \varepsilon(t) - 0.6\varepsilon(t-5),$$

where $\varepsilon(t) \in N(0; 5.4)$.

*Models for time series ntr (t) data*

Models for time series {*ntr(t)*} were also constructed using an algorithm similar to.

After identifying and correcting anomalous points, a trend can be identified according to the time series {*ntr(t)*} data:

$$\widehat{ntr}(t) = 7.86 - 0.01t \tag{3}$$

The negative coefficient in front of *t* in (3) indicates a decrease in the number of messages with a neutral attitude to the construction. The model was checked for adequacy. In particular, the hypothesis of the inadequacy of model (3) according to Fisher's criterion was rejected at a significance level of p = 0.04, which indicates the reliable quality of the constructed model. To construct a model of the random component of time series $\widehat{E}_{ntr}(t)=ntr(t)-\widehat{ntr}(t)$, estimates of the autocovariance and partial autocovariance functions are found. Based on the results of the found estimates of these functions, the structure of the autocovariance model is chosen.

*For the remainders of the series, an ARIMA (1,0,0) model was constructed.*

$\widehat{E}_{ntr}(t)=0.4E_{ntr}(t-1)+\varepsilon(t)$, where $\varepsilon(t)\in N(0;1)$.

The models constructed allow making time series predictions several steps ahead.

*2.5.2. ODE Models*

To analyze the behavior of a dynamic system, it is important to have continuous mathematical models. When building models using ODE, data transformations are used. Within the framework of the problem under consideration, we assumed that the percentage of all three groups of the part of the society that is not involved in social networks is in the same percentage as the one that is involved. Due to the fact that we are primarily interested in the dynamics of the number of actors with a positive and negative attitude, and given that the activity of posts varies depending on the day of the week, holidays, etc. the following normalization is adopted. Two new variables have been introduced: x(t)=poz(t)/ntr(t), y(t)=neg(t)/ntr(t). In table 3, a fragment of the initial data x(t), y(t).

**Table 3.** Fragment of initial data x(t), y(t)

| t | x | y |
|---|---|---|
| 1 | 0,139394 | 0 |
| 2 | 0,240876 | 0 |
| 3 | 0,22549 | 0 |
| 4 | 0,21875 | 0 |
| 5 | 0,032258 | 0,096774 |
| 6 | 0,382979 | 0,021277 |

General statement of the problem. Time series {x(t)}, {y(t)}, where t=1,.., N, are given, which characterize the level of positive and negative attitude towards the project, respectively. The sampling step is constant. It is necessary, according to these data, to build dynamic models for forecasting and analyzing the situation.

At the first step, the data were smoothed using convolutional neural networks, then estimates of the parameters of differential equations were found using the algorithm of the Nelder-Mead method. As a result of the implementation of the algorithms, several variants of models were obtained in the form of systems of differential equations. One of the equations looks like this:

$$\begin{cases} \dfrac{dx}{dt} = 0.91x - 0.15y \\ \dfrac{dy}{dt} = 0.1x + 0.3y \end{cases}$$

The constructed model was studied for structural stability. Eigenvalues of the determinant of the system λ1=0.84 , λ2=0.36. Therefore, the rest point (0, 0) is an unstable node. This indicates that as t increases, points arbitrarily close to the origin are removed from ε, the neighborhood of the origin. Because of this, in order to track the dynamics of the development of the situation, it is necessary to use parallel models, in particular, models for forecasting time series. It can also be noted that estimates of the coefficients of the system of differential equations indicate that the series {y(t)} grows faster than {x(t)}.

 

*2.5.3. Mathematical model with LSTM*

Traditionally developed for 2D image data, LSTMs can be used to model univariate and multivariate time series forecasting problems. The LSTM network is one of the modifications of recurrent neural networks most commonly used in deep learning. The work was carried out in the Google Colaboratory environment (a Google Research product that is used to write code), the models were implemented and trained using machine learning libraries such as: tensorflow, keras, sklearn. Additionally, the mathematical libraries numpy, pandas and matplotlib were used for calculations and plotting.

A recurrent neural network (RNN) was built, namely a modification of the LSTM. The neural network architecture looks like this:

- ADAMAX optimizer
- learning rate 0.001
- LSTM modification
- activation function - ReLU.
- error function - MSE (root mean square error)
- metric for quality assessment - MAE (mean absolute error)
- number of learning epochs - 100
- batch size - 16

In our problem, the data is considered in the form of a multivariate time series. Data with a window of 4 were fed to the input of the neural network. The choice of the size of the number of input time steps has an important impact on how much data array will be used for training. An estimate of the size of the number of input time steps is obtained using autocorrelation estimates. The work was carried out in the Google Colaboratory environment, the models were implemented and trained using machine learning libraries such as: tensorflow, keras, sklearn. Additionally, the mathematical libraries numpy, pandas and matplotlib were used for calculations and plotting. When training the CNN, the ADAMAX optimizer was used, and ReLU was used as an activation function. The following learning outcomes have been obtained:

```
Epoch 98/100
164/164 - 0s - loss: 0.0140 - 405ms/epoch - 2ms/step
Epoch 99/100
164/164 - 0s - loss: 0.0141 - 404ms/epoch - 2ms/step
Epoch 100/100
164/164 - 0s - loss: 0.0139 - 396ms/epoch - 2ms/step
 Train Score: 0.18 RMSE
 Test Score: 0.30 RMSE
```

*2.5.4. Model Building Results*

The constructed ARMA, ODE, LSTM models were compared on the test set (Table 4). In the Test Error column, the percentage of points where the calculation error is greater than the allowed threshold value. According to the performed calculations, LSTM has the best result in terms of accuracy and computational speed. The ARMA and ODE models are more suitable for analyzing the dynamics of the situation.

**Table 4.** Model comparison

| | Test Error |
|---|---|
| ARMA | 10% |
| ODE | 8% |
| LSTM | 5% |

 

## 3. CONCLUSION

The study showed the consistency of the results obtained during the application of various types of models using cognitive calculations based on speech data of social media actors to reveal the presence/absence of social tension in the area of the Nizhegorodskaya TIH construction.

Semantic analysis of the content involving neural network technologies showed a neutral attitude of the residents towards the project implementation, the absence of social stress in the construction areas. The content ranking is topped by official messages announcing the plans of the Moscow authorities to improve the transport system in the area and the construction progress. The users' digital footprints confirm the neutral perception and assessments of the residents' needs to change the traffic situation after the completion of the project.

However, slight concerns can be caused by the dynamics of messages with various sentiment types, which demonstrates an increase in negative messages and a decrease in neutral and positive references to the implementation of the Nizhegorodskaya TIH project. Meanwhile, the insignificance of quantitative indicators does not give grounds for negative assumptions.

The constructed mathematical models of time series according to the intensity of messages with a neutral, positive and negative attitude to the construction make it possible: 1) to assess the dynamics of these series quantitatively; 2) to predict the values of time series by several steps ahead. The results of the study are important for making management decisions in identifying and preventing urban planning conflicts.

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