Forecasting Efficiency of Programs and Optimization of Local Budgets in Smart Cities for a Better Quality of Life

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Abstract - This paper presents the results of developing a machine learning model of migration of citizens to districts of the city of St. Petersburg. The models were built based on the dynamics of economic reporting indicators of districts, the territorial characteristics of municipal districts, and the characteristics of the flow of population itself. Correlations of these indicators with the quality of life were determined. Quality of life is certainly related to the characteristics of migration, emigration, and their ratio, as well as their dynamics as it is an objective indicator of the attractiveness of the municipal district. On the basis of the data of 2118 indicators in the dynamics from 17 to 20 years for 111 municipal districts managed to develop a model of machine learning in the indicator R-Squared: 0.74, RMSE: 414.73. Thus, it was possible to reveal the most significant indicators for improvement of quality of life of the population considering specificity of municipal district, structure of living population and structure of expenses in the unified system. The given model can be applied both for forecasting of quantity of migration and structure, and for decision-making on improvement of quality of life of the city population in view of specificity, dynamics, and budget of municipal districts. The results can be useful for regulatory policy and optimization of legal regulation.

I. Introduction

Each city is unique in its characteristics, dynamics, rhythm, population composition, and quality of life criteria. Most of the population in developed countries lives in cities and urban agglomerations, while developing countries are picking up the pace of urbanization. In this regard, the topic of the urban environment and its impact on people is relevant at the moment.

The integration of AI in city management is promising and one of the key technologies for the development of a smart city. Artificial intelligence technologies will clearly help society to develop, especially in several sectors, including transportation, healthcare, education, city tourism [1], [2]. The following benefits of using AI in smart cities are identified: 1) Improved decision-making; 2) Improved mass data processing; 3) Increased economy and productivity; 4) Understanding complex and pressing issues; 5) Increased monitoring; 6) Improved citizen interaction; and 7) Help with environmental conservation. Also artificial intelligence (AI), machine learning (ML), and deep learning with reinforcement (DRL) will play an important role in intelligent transportation systems, cybersecurity, and smart healthcare [3]. There are many definitions of quality of life, but in our opinion the most comprehensive definitions of quality of life have been provided in studies [4]: "Quality of life is the degree to which an individual's objective needs are met in relation to personal or group perceptions of subjective well-being" and [5]: "Quality of life is an integral part of a person's psychological and physical well-being and is closely related to concepts such as satisfaction, human development, happiness, and well-being.". The spatial structure of the city is related to the quality of life and sustainability of cities, as it has a strong influence on socio-economic functions, but does not fully determine them. [6]. Also quality and meaningful urban space has a positive impact on health, social, economic and environmental aspects in the short, medium and long term among all citizens of different socioeconomic [7]. In this paper we analyzed a significant number of indicators that can affect the quality of life in an urban environment. By using machine learning methods, it was possible to obtain global and local interpretability of a significant number of quantitative indicators in dynamics in a single system and in relationship, rather than in pairs, which is the value of this approach.

II. Related Works

Among studies of the quality of life of the urban environment, there are rarely works devoted to using methods of machine learning and artificial intelligence. However, from the many studies of the urban environment, one can emphasize a variety of metrics and approaches, such as that the urban environment affects health [8]–[10], city transportation [11]–[13], social life and personal relationships [14]–[16]. Liveable cities can be considered those that strive for the well-being of all their residents [15], [17], [18]. Metrics are an important part of research on quality of life and the urban environment.

The literature on the concept of quality of life demonstrates its complexity, as it is described as a multifaceted concept that combines complex indicators of both objective and subjective [4]; [19], [20]. Research on quality of life in urban settings has focused on issues ranging from vegetation, relationships with neighbors, and safety. For example, the layout of neighborhood lots is important to quality of life, which includes requirements related to lot size, residential diversity, and even building density. According to the studies [21] and [22] housing and street design that promotes social control leads to less graffiti and litter on the streets.

Satisfaction with commuting, neighbors, and housing are significantly related to subjective well-being [23]. Neighborhood satisfaction has a direct impact on quality of life and reinforces the impact of the physical factor of safety on quality of life [24]. Satisfaction with travel has no significant effect on life satisfaction scores [25]. It has been suggested that satisfaction with travel mainly has an indirect effect on life satisfaction through participation in and satisfaction with leisure activities [26]. On the other hand, long commute times are associated with lower job satisfaction [27].

An interesting correlation between technology and quality of life can be noted: "digital citizens" are happier and more appreciative of life in regions/cities with technological potential. Satisfaction with life increases with greater use of technology in the region[28].

According to a new review [29] embedded urban environment affects subjective well-being. This indicator was divided into seven domains: travel, leisure, work, social relationships, housing well-being, emotional responses, and health.

The complexity of measuring the quality of life in cities and neighborhoods seems obvious: the variables to be considered are numerous, deeply interrelated, and most often subjective.

There are many indicators that focus on measuring the quality of life around the world, but there are significant differences in methodology and results among them. Despite this, the main components of the survey can include the economy, health care, education, and life expectancy of the population. Recently, in addition to achieving growth in quantitative indicators, qualitative growth, such as the quality of life of residents, has been sought as an equally important factor in the sustainability of cities.

In Table 1 we can see the studies, which were aimed at a comprehensive analysis of the quality of life, rather than individual aspects of it. The research was conducted both at the municipal level and at the regional and country level.

TABLE I. ARTICLES ANALYZING COMPREHENSIVE ASPECTS OF QUALITY OF LIFE

Doumpos et al., 2020 [30]	The 2012 dataset was used for the analysis, based on key performance indicators. The indicators were mainly related to the number of benefits per inhabitant. The correlation of quality-of-life indicators with the financial sustainability of municipalities was also investigated. The results showed that the quality of life differs not only by region of France, but also by the size of the municipalities. In addition, it was found that indicators of the quality of life of French municipalities are related to financial aspects.
Anna Papachristou & Rosas-Casals, 2019 [31]	In this article, the authors compared the temporal evolution of happiness domains and urban studies into dynamic networks, by analyzing keyword matches in the article. It was found that while quality of life and well-being are strongly correlated with some well-defined urban categories, other concepts related to happiness, such as subjective well-being or happiness itself, are on the periphery, where their influence is minimized.
Dardha & Rogge, 2020 [32]	The study analyzed well-being in 349 regions of the Organization for Economic Co-operation and Development countries. Three multidimensional indicators of regional well-being were calculated: the index of material well-being, the index of quality of life, and the index of subjective life satisfaction. It was also found that the three areas of well-being differed significantly, not only between countries, but also within countries.
Greco et al., 2020 [33]	In this study, the authors used the database of the Organization for Economic Co-operation and Development countries' Better Life Index, as well as the database of a survey of people who self-selected to prioritize a better life out of 11 dimensions. These preferences are expressed as points in a Euclidean K-dimensional space in which each dimension is a particular aspect of well-being. Then, for everyone, the distance between his or her optimal combination of well-being and the combination provided by the bodies is calculated. The highest score is obtained by those countries whose indicators are close to the ideal citizens. Countries with lower levels of democracy have high levels of social welfare losses. Also, countries with a high mismatch are the countries with the worst best life index.
Decancq, 2017 [34]	In this article, the author attempted to develop a distributional index of a better life and, through analysis, presented the first results. The Nordic countries ranked first on the distributional index of a better life, while Mexico, Chile, Brazil, Greece, the Russian Federation, and Turkey ranked last. These countries have both low average scores on each of the dimensions and high levels of multidimensional inequality.
Murgas & Klobucnik, 2016 [35]	The study calculated the index of quality of life of all municipalities in the Czech Republic (6251) based on 10 gold standard indicators and derived indices of higher hierarchical levels of districts and regions and the expression of their spatial differentiation. It was found that

	the quality of life is not related to the size of the municipality.
Kaklauskas et al., 2018 [20]	This paper evaluated the quality of life and ranked European cities using the QLI method and the new Kaklauskas method - INVAR (Project Utility and Investment Value Assessment together with Recommendations). The conformity assessment of the results obtained by both methods and sensitivity analysis were performed based on the quantitative tool proposed in the article. A good level of rank correspondence was obtained. The INVAR method complements the QLI method by providing quantitative recommendations for the analyzed cities on quality-of-life indicators, which allows the analyzed city to improve its ranking to the desired level.
Weziak-Bialowolska, 2016 [19]	The paper presents a study based on a survey of the opinions of 41 thousand residents from 79 European cities, which allows us to analyze the relationship between the characteristics of citizens, the contexts of neighborhoods and cities and satisfaction with life in the city. It was found that a sense of security in the city, financial situation and place of residence affect satisfaction with life in the city. Questions related to public transportation, green spaces, availability of retail outlets, air quality, people living in the city and in the neighborhood, etc. have the opposite effect. Issues related to health services, sports facilities, public spaces, noise, and cleanliness have a neutral effect. Neighborhood issues were also significantly associated with satisfaction with living where one lives, although insignificant in the assessment of the city's outlook
Gou et al., 2018 [36]	In this study, conducted in Hong Kong, four areas were analyzed which, according to WHO, are related to quality of life: Physical Health, Mental Health, Social Relationships, and Environment. It was found that the environment and its constituent aspects of the housing environment were found to be the most influential factor in overall quality of life, especially in the low-income sector.
Macke et al., 2018 [37]	The purpose of this paper was to assess the perception of quality of life in a smart city and to analyze the main elements of citizens' satisfaction with their hometown. Through interviews with residents, the authors identified four main areas of quality of life: social-structural relations, environmental well-being, material well-being, and community integration.
Faka et al., 2021 [38]	To assess the quality of life in cities, a comprehensive index is constructed using multi-criteria analysis. For this purpose, factors controlling the quality of life, such as building area, natural, socio-economic, and cultural environment, infrastructure and services, and quality of housing were analyzed in a GIS environment. The comparison of this index led to the identification of areas with different levels of quality of life.
Balestra et al., 2018 [39]	The authors analyzed the well-being preferences of 88,000 people using the Organization for Economic Co-operation and Development countries' web-based Better Life Index tool, which allows users to create their own composite well-being index by assigning weights to each of 11 dimensions of well-being structure. The paper concludes that health, education, and life satisfaction are the most important dimensions in Organization for Economic Co-operation and Development countries.

In addition to quality of life research, work has been done to create new methods for assessing the quality of life and to identify meaningful criteria [20], [34], [40]–[42] or evaluate already existing methods [43]. There have also been studies in which the authors analyzed the impact of decisions on quality of life [44].

The most common indicator is the OECD Better Life Index, which covers many countries around the world. It is made up of a survey of participants on 11 criteria, which they rank. This index is quite subjective, which does not always reflect the real picture of the world.

To improve the standard of living of citizens and increase the level of sustainability of cities, many governments in recent years have been considering the implementation of the concept of a smart city. To do this, they are introducing various technologies for working with big data, which, support the components of a smart city. In the paper Ferro De Guimaraes et al., 2020 the authors concluded that the quality of life is indeed affected by elements of the smart city.

According to a report by Deloitte Consulting Group [46]: "A city is smart when investments in (i) human and social capital, (ii) traditional infrastructure, and (iii) breakthrough technology contribute to sustainable economic growth and a high quality of life while managing natural resources wisely through collective management."

Integration of information technology in city management is promising and one of the key technologies for the development of a smart city [1], [2]. In the paper Ben Rjab & Mellouli [2] came to the conclusion that artificial intelligence technologies will clearly help society develop, especially in several sectors, including transportation, healthcare, education, tourism, etc. The authors identified the following benefits of using AI in smart cities: 1) Improved decision-making; 2) Improved mass data processing; 3) Increased economy and productivity; 4) Understanding complex and pressing issues; 5) Increased monitoring; 6) Improved citizen interaction; 7) Helping to preserve the environment. Also artificial intelligence (AI), machine learning (ML), and deep learning with reinforcement (DRL) will play an important role in intelligent transportation systems, cybersecurity, and smart healthcare [3]. Thus, this work contributes to advances in urban environmental analysis and modeling, not only with respect to the development of the application of machine learning methods, but also with respect to the uniqueness of the data and the city of St. Petersburg.

III. Methods

Data on the reporting of medical organizations were collected from the Unified Interagency Information and Statistical System (EMISS), which was developed as part of the federal target program "Development of State Statistics of Russia. Data on 2011 reporting indicators of MOE were collected in a single dataset with migration data.

The analysis included 20 migration indicators of the structure of migration flows, population size and density, data on 568 characteristics and composition of economic entities, as well as 1444 indicators of economic activity of municipal districts, characterizing all areas of municipal district development, including activities in the field of culture, construction, communication, business, transport, and environment.

The data were collected and structured as follows: the data were measured by region and reporting period (year), with the year and municipality as the row and the indicator as the column. Next, the median blanks were filled in, the sample was divided into a test sample (20 percent) and a training sample (80 percent), after which a regression model was trained on the obtained data by XGBoost Regression with the best parameters XGBRegressor (base_score=0.5, booster=None, colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1, importance_type='gain', interaction_constraints=None, learning_rate=0.300000012,max_delta_step=0, max_depth=6,min_child_weight=1, missing=nan, monotone_constraints=None, n_estimators=100, n_jobs=0, num_parallel_tree=1, random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method=None, validate_parameters=False, verbosity=None))

Next, the RMSE and R-Squared error were calculated, predictor significance was calculated, and then interpretation was performed.

IV. Results

We developed a gradient boosting model based on 2221 indicators on the "Internal Migration Growth" target. Regularization was performed to improve the model. The best parameters are as follows XGBoost Regression with best parameters XGBRegressor (base_score=0.5, booster=None, colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1, importance_type='gain', interaction_constraints=None, learning_rate=0.300000012,max_delta_step=0, max_depth=6,min_child_weight=1, missing=nan, monotone_constraints=None, n_estimators=100, n_jobs=0, num_parallel_tree=1, random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method=None, validate_parameters=False, verbosity=None)).

The R-square error is presented in the Fig. 1.

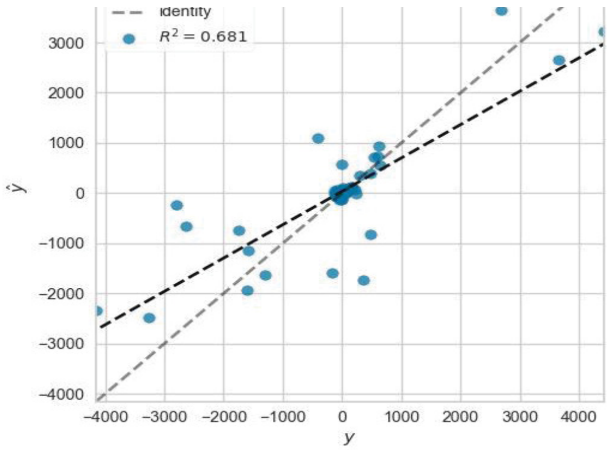

Fig 1. R-square error in the gradient-busting migration model

The calculation of features importance was calculated using the F1-score metrics and the Shapley index. The results of for F1 are shown in Figure 2, and the results for the Shapley index in the Fig. 3.

Among the main indicators contributing to the migration model are the indicator of the contribution of the municipality to fixed capital, environmental indicators (pollution in the area, current spending on environmental protection), the cost per square meter in the municipality, the cost of law enforcement, which indicates the conscious nature of migration to counties where authorities develop economy, spend on ecology and law enforcement, which determines the demand and cost of housing on the one hand, on the other hand t cost of housing. It is worth noting that the number of commissioned spaces is not the main indicator of migration, which is also an interesting fact for further study.

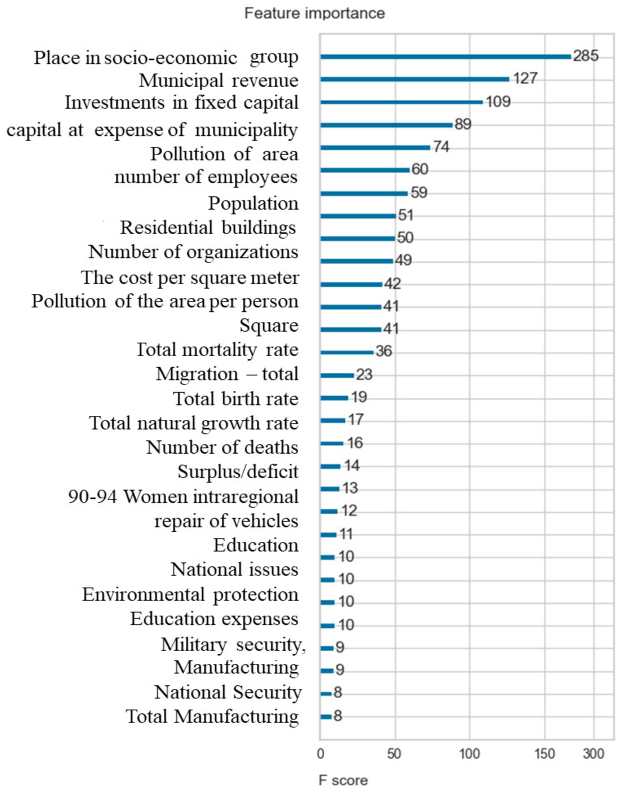

Fig. 2. Features importance in the gradient-busting model on the rate of population migration to municipal districts.

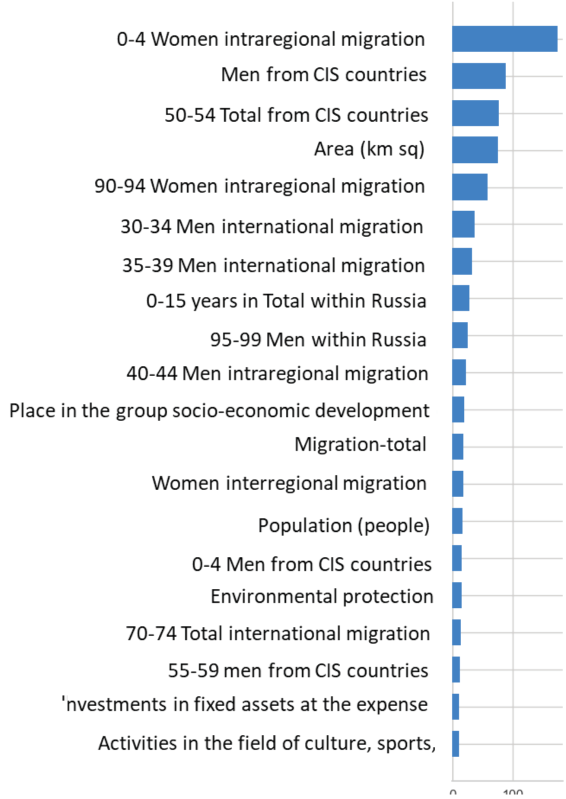

Fig. 3. Features importance in the gradient-busting model on the indicator of population migration to municipal districts

An interesting fact found in the results of the calculation of the significance of predictors based on the Shaple index is that it also identified an indicator of the development of the municipal district in the field of culture, sports, leisure, and entertainment. Also noteworthy is the indicator of women 0-4, which indicates the predominance of female children under 4 years of age in the flow of migration. Also in this interpretation we can see the structure of the flow, which consists of older men from the Commonwealth of Independent States (CIS) countries, and women over 90 years from the regions of Russia.

Thus, it can be concluded that the main needs in the most sought-after municipalities are medical care for these groups of patients, as they fall into the relevant health risk groups. Recommendations to increase the attractiveness of the municipality and improve the quality of life in this case can be optimization of expenditures of municipal districts in the direction of increasing spending to cover the needs of these population groups, namely for medical care. As we can see from both methods of interpretation, the indicators related to medical care and the increase in the level of expenditures specific to these groups are absent in the first ten significant predictors. To improve the quality of life of these main groups, a revision of current indicators and their dynamics is required.

V. Conclusion

This one identifies the main indicators affecting the attractiveness of the municipality for migration, determines the structure and composition of the flow of migration flow and the main groups that require special attention in solving the problems of improving the quality of life in the urban environment. Such groups are children and elderly people who require appropriate medical services and special facilities in the urban environment for movement. Thus, global (general) indicators and local (special) indicators influencing the attractiveness, and thus, reflecting the quality of life on the one hand, and changing the requirements for the urban environment, on the other hand, the results of the dynamics and changes in the structure of the flow of the population were determined.

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