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Algorithm for Searching Weight Indicators in the Reproduction Cycles Proportions of Different Sectoral Localization at the Regional Level

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ABSTRACT

The purpose of the study is to develop an algorithm for finding weight indicators in the proportions of reproductive cycles of various industry localizations to determine the integral coefficient of the state of reproductive proportions. Regression analysis methods were used for data processing and analysis, and the construction of digital models for optimizing weight indicators is based on the use of "Lasso", "Random Forest", and "Ensemble" models. As a result, a Python programming language code algorithm has been formed, which allows the use of econometric modeling to search for optimal weight values and to form integral coefficients with mathematical justification. The use of the developed algorithm will allow the development of a system for managing reproductive processes at the regional level with the aim of forming strategies for socio-economic development based on the identification of standard proportions of reproductive cycles of various industry localizations.

INTRODUCTION

Modern economic conditions require highly efficient management systems for regional reproductive processes. The research on optimal proportions of reproductive cycles in various sectors at the regional level remains important. Current methods often overlook modeling, and strategies for determining integral coefficients rely on stagnant expert assessments. As reproductive cycles may differ depending on regional factors and specific economic conditions, it's crucial to develop methodologies that consider these variances. Econometrically justified approaches will promote more rational resource use and enhance the accuracy of modeling.

The aim of the study is to develop and implement an algorithm for finding weight indicators in the proportions of reproductive cycles of various industry localizations, which will allow to determine the integral coefficient of the state of reproductive proportions and formulate socio-economic development strategies at the regional level. To achieve this goal, it is proposed to develop a mathematical model for determining weight indicators of proportions of reproductive cycles, apply econometric methods for data processing and analysis, construct digital models for optimizing weight indicators, develop a Python programming language code algorithm for modeling and searching for optimal weight values.

The study employed methods of regression analysis and modeling using "Lasso", "Random Forest", and "Ensemble" models. The subject of the study were reproductive processes of various industry localizations at the regional level. The proposed algorithm is integrated into the code in the Python programming language, which allows, through econometric modeling, to set the most optimal weight values and to form mathematically justified integral coefficients. The results of the study contribute to the development of the system for managing reproductive processes at the regional level. They are also useful for forming strategies for economic development based on identifying standard proportions of reproductive cycles of various industry localizations, which allows for increasing the efficiency of resource use and making reproductive processes balanced and stable.

1. RESEARCH METHODOLOGY

The distribution of resources and management of reproductive processes in the regional economy attract significant attention from researchers from different fields. However, there are no unified approaches to this issue yet. It is proposed to use the developments of researchers that can be used to develop new approaches capable of solving various problems in the regional economy.

1.1 Digital Technologies in Solving Economic Problems

Global digitization and the knowledge economy offer an opportunity to formulate strategies for sustainable competitive advantage. Cross-industry and interdisciplinary methods are emerging, transforming reproductive processes in regional economies by adapting digital technologies to problem-solving. The focus has shifted towards the intellectual nature of these processes (Dmitriev et al., 2020; de Pablos, 2020). Resource optimization models allow the integration of digital technologies into resource approaches for analyzing material and immaterial aspects of reproductive processes. In particular, a resource-oriented linear programming model actively uses mixed integer or stochastic models (Maiti et al., 2020; Nikolova et al., 2017). In developing methods for assessing the conditions for implementing innovative activity in the region, models should be developed considering knowledge management factors in a digital environment, which is relevant in the context of activating innovation processes (Babskova et al., 2019; Konnikov et al., 2021).

Analyzing the characteristics and structure of the regional resource potential can rationalize their use. Identification, classification, and decomposition of the resource potential and territorial capitalization are required (Lyshchikova et al., 2016). The growing emphasis on investment and innovative development necessitates sensitive indicators for technological specifics of territorial economic systems. This requires the integration of economic-mathematical tools into multi-level management systems (Iastremska et al., 2019; Rodionov et al., 2018, 2022). In the evolution of regional innovation policy, advanced management practices are developed at the regional level. The stability of management depends on the choice of indicators. Econometric modeling can rationalize analytical processes (McCann & Ortega-Argiles, 2013; Tuo & He, 2021). Management methods are developed to maximize productivity and minimize costs, considering strategic needs. This rationalizes regional policy (Zaytsev et al., 2020).

The adoption of digital solutions in business practices allows for market management models based on factor analysis. In a changing social context, analysis of economic and political structures can foster innovative perspectives (Elder-Vass, 2016). To maximize efficiency, it's necessary to use the intellectual capital of economic systems, rationalizing management systems, and setting trajectories for innovative economic growth (Dmitriev & Zaytsev, 2021; Zhilenkova et al., 2019).

1.2 Reproduction Cycles in the Regional Economy

Reproduction is a recurring process of producing, distributing, exchanging, and consuming products and services. It represents the transformation of resource potential into final consumption over time. The efficiency of a regional economy hinges on the seamless integration of these stages (Bergstrom & Randall, 2016; Klosterman, 1994; Skousen, 2007). Within each stage, relationships emerge that ensure the reproductive cycle and balance of the territorial system. If any stage is undeveloped, the whole system's efficiency is compromised. Typically, the cycle starts with production, transforming natural resources to meet needs. With digitization and the rise of the information society, production integrates scientific ideas, equipment, and technology, becoming more efficient (Atkinson & Ezell, 2012).

The regional reproductive process, part of social reproduction, consolidates the reproductive efforts of enterprises to boost the region's economy. It operates through reproduction cycles, supplying the regional economy with products, services, and essential conditions. These cycles encompass finance, investments, food, resources, services, infrastructure, and knowledge, forming an integrated system in constant interaction. Reproductive cycles underpin the socio-economic development of a region, ensuring continuous interaction among its economic players. These cycles, as an independent subsystem, maintain the ongoing functions and relationships within the regional system. Each level of the regional economy has its distinct reproductive cycles, confined within its territorial boundaries. Regional reproductive indicators provide insights into the relationship between regional reproductive cycles, resources used, production type, and infrastructure development. These proportions encompass all economic aspects, including industry, production, consumption, costs, and outcomes. Analyzing these proportions is crucial for regional economic management, as they reflect economic relations, impact the reproduction process, assess the regional system's status, and determine its efficiency (Yakimenko et al., 2013).

Analysis of reproductive proportions examines the economic structure of regions or countries, identifying the shares of different sectors in production or gross product. This analysis informs about economic dynamics, highlights strengths and weaknesses, and pinpoints prospective industries and strategies. The proportions of the regional reproductive process include: general economic, structural, foreign economic, socio-economic, economic-demographic, economic-ecological, and financial-economic (Malyshev & Kamalova, 2012; Marshalova & Novoselov, 1998). Reproduction cycles, while autonomous, intertwine within a territory, aligning the objectives of various stakeholders with regional development goals. This holistic view facilitates regional problem-solving, enhances enterprise opportunities, and elevates the residents' quality of life.

2. METHODOLOGY

The search for weight indicators in integral indicators characterizing the proportions of reproductive cycles of various industry localizations at the regional level can be carried out using various methods, for example through expert assessment, analytical methods (Analytic Hierarchy Process, Weighted Aggregated Sum Product Assessment), machine learning methods (random forest or gradient boosting), balancing principles, sensitivity analysis, principal components, etc. (James et al., 2013). In the study, it is proposed to use regression analysis methods - Lasso regression, Random Forest, and Ensemble. A model with L1 regularization (Lasso) is a linear regression regularization method that adds L1 regularization. Lasso regression allows you to find weight coefficients, nullifying some of them, thereby performing the selection of the most important features and solving the problem of multicollinearity (Hastie et al., 2001).

The linear model with L1 regularization is used for feature selection and dimensionality reduction. The target variable is predicted as a linear combination of features with corresponding weights. It adds a penalty term equal to the absolute value of the weights of the features multiplied by the parameter α to the loss function. As a result, Lasso nullifies the weights of insignificant features, which leads to the selection of significant features for predicting the target variable (formula 1). During training, Lasso minimizes the loss function, which includes the mean square error (MSE) between the predicted values and the true values of the target variable, as well as a penalty term for the absolute values of the feature weights (formula 2). The larger α is, the more weights are nullified, which leads to the selection of significant features.

$$y = w1 \times x1 + w2 \times x2 + \ldots + wn \times xn + b, \ (1)$$

$$Loss = MSE + \alpha \times \Sigma |wi|, \ (2)$$

y – prediction of *th e* target variable; *w1, w2, ..., wn* – weights of the features *x1, x2, ..., xn*; *b* – bias; *α* – regularization hyperparameter (alpha), which controls the influence of L1 regularization;

Random Forest is an ensemble algorithm that combines multiple decision trees to construct a sophisticated model. Within the framework of regression analysis, the random forest builds several trees, and each tree predicts a numerical value (continuous target variable). Then the results of all the trees are averaged to get the final prediction (Breiman, 2001; Dietterich, 2000; Gall et al., 2012). The Random Forest model uses the Bootstrap Aggregating (bagging) method, creating random subsamples of data and training a separate tree on each one. Then the results of each tree are combined to obtain the final prediction. The Random Forest method allows reducing overfitting, improving generalization ability, and evaluating the importance of features (formula 3).

$$y = (h(x;\ \theta1) + h(x;\ \theta2) + \ldots + h(x;\ \theta N)) \,/\, N, \ (3)$$

h(x; θi) – prediction of the *i*-th tree; *N* – the number of trees; *θ1, θ2, ..., θN* – parameters of the trees.

Ensemble is an extension of the random forest, where multiple random forests are used, trained on different subsets of data or with different parameters. During the prediction process, the results of each random forest are combined, for example, averaged or weighted, to obtain the final ensemble prediction (Bishop, 2006; Murphy, 2012).

For the Ensemble model, there are no specific mathematical formulas, as it is a combination of several random forests. If there are *K* random forests, trained on different subsets of data or with different parameters from these random forests, the target variable is predicted for each new observation. The ensemble learning procedure: create *K* different random forests, each with a different set of data or parameters; train random forests on the corresponding data; for a new observation, predictions of the target variable are made from each of the *K* random forests; combine predictions through averaging or weighting; the final ensemble prediction is obtained as the average of the predictions of *K* random forests, divided by the number of models *K*. It is proposed to consider the ensemble prediction for a new observation *x* by formula 4.

$$y\_ensemble = (1/K) \times \Sigma\, y\_i(x), \ (4)$$

y_ensemble – the final ensemble prediction; *y_i(x)* – prediction of the *i*- th random forest for the input data *x*; Σ –the sum over all *i* from 1 to *K*.

3. RESULTS & DISCUSSION

3.1 Standardized Definition of Weight Indicators

In the first stage of the algorithm, it is proposed to define standardized weight indicators in the proportions of reproductive cycles of various industry localizations at the regional level. For the construction of the algorithm, the following proportions are allocated: general economic, structural, socio-economic, economic-demographic, economic-ecological, financial-economic (embedded in DataFrame using the data variable). Weight coefficients are found according to standard algorithms. It is proposed to form digital algorithms using code in the Python programming language. The methods can also be used in combination to average the results for a more accurate analysis. When analyzing the structure of a region's economy and the industries present in it, the method of least squares often appears to be the most promising, due to its ability to minimize the total prediction error.

After determining the weight indicators using statistical methods, it is necessary to proceed to the adaptation of machine learning methods, as this will help to more objectively assess the economic dynamics of the region, taking into account possible interrelations between industries. It should be noted that for the effective application of machine learning methods, it is necessary to extract large amounts of data. This approach will allow not only to analyze the situation, but also to train algorithms, as well as to carry out subsequent validation of the results. As a result, the accuracy and validity of conclusions about the economic dynamics of the region will increase.

3.2. Determining weight indicators using machine learning methods

At the second stage of the algorithm, it is proposed to use standardized weight indicators in proportions of reproduction cycles of various sectoral localization at the regional level for their modification by machine learning methods. The following proportions are also identified for algorithm construction: macroeconomic, structural, socio-economic, economic-demographic, economic-ecological, and financial-economic. Information by regions is also added, which allows accounting for additional dependencies. This data is included in a DataFrame using the 'data' variable. Weight coefficients are found using the 'Lasso', 'Random Forest', and 'Ensemble' algorithms. It is proposed to form digital algorithms using the Python programming language (table 1).

Table 1. Search for weight indicators using machine learning methods

```
# Import the necessary libraries
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split

# Data preparation
data = {'Years': [], 'General Economic': [], 'Structural': [], 'Socio-economic': [], 'Economic and demographic': [], 'Economic and environmental': [], 'Financial and economic': []}
df = pd.DataFrame(data) # Creating a DataFrame

# Extraction of features and target variable
X = df.drop(columns=[ Region', 'Years', 'Integral coefficient])
y = df['Integral coefficient']

# Splitting data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Data normalization
scaler = StandardScaler()
X_train_normalized = scaler.fit_transform(X_train)
X_test_normalized = scaler.transform(X_test)

# Lasso
alpha_values = np.logspace(-4, 0, 100)
lasso_model = Lasso(max_iter=100000)
grid_search_lasso = GridSearchCV(lasso_model, {'alpha': alpha_values}, cv=2)
grid_search_lasso.fit(X_train_normalized, y_train)
best_alpha = grid_search_lasso.best_params_['alpha']
lasso_model_best = Lasso(alpha=best_alpha)
lasso_model_best.fit(X_train_normalized, y_train)
weights_lasso = pd.DataFrame({'Feature': X.columns, 'Weight_Lasso’: lasso_model_best.coef_})
print("Best alpha value for Lasso:", best_alpha)
print("Feature weights for Lasso:")
print(weights_lasso)

# Random Forest
param_grid_rf = {'n_estimators': range(30, 201, 5), 'max_depth': range(1, 11)}
rf_model = RandomForestRegressor()
grid_search_rf = GridSearchCV(rf_model, param_grid=param_grid_rf, cv=2)
grid_search_rf.fit(X_train_normalized, y_train)
best_n_estimators_rf = grid_search_rf.best_params_['n_estimators']
best_max_depth_rf = grid_search_rf.best_params_['max_depth']
```

```
rf_model_best = RandomForestRegressor(n_estimators=best_n_estimators_rf, max_depth=best_max_depth_rf)
rf_model_best.fit(X_train_normalized, y_train)
weights_rf = pd.DataFrame({'Feature': X.columns, 'Weight_RF': rf_model_best.feature_importances_})
print("\nBest number of trees for Random Forest:", best_n_estimators_rf)
print("Best maximum depth for Random Forest:", best_max_depth_rf)
print("Feature weights for Random Forest:")
print(weights_rf)
# Ensemble
ensemble_model = RandomForestRegressor()
grid_search_ensemble = GridSearchCV(ensemble_model, param_grid=param_grid_rf, cv=2)
grid_search_ensemble.fit(X_train_normalized, y_train)
best_n_estimators_ensemble = grid_search_ensemble.best_params_['n_estimators']
best_max_depth_ensemble = grid_search_ensemble.best_params_['max_depth']
ensemble_model_best = RandomForestRegressor(n_estimators=best_n_estimators_ensemble,
max_depth=best_max_depth_ensemble)
ensemble_model_best.fit(X_train_normalized, y_train)
weights_ensemble = pd.DataFrame({'Feature': X.columns, 'Weight_Ensemble': ensemble_model_best.feature_im-
portances_})
print("\nBest number of trees for Ensemble:", best_n_estimators_ensemble)
print("Best maximum depth for Ensemble:", best_max_depth_ensemble)
print("Feature weights for Ensemble:")
print(weights_ensemble)
# Evaluation of MSE for each model on testing data
y_pred_lasso = lasso_model_best.predict(X_test_normalized)
mse_lasso = mean_squared_error(y_test, y_pred_lasso)
print("\nMSE for Lasso model:", mse_lasso)
y_pred_rf = rf_model_best.predict(X_test_normalized)
mse_rf = mean_squared_error(y_test, y_pred_rf)
print("\nMSE for Random Forest model:", mse_rf)
y_pred_ensemble = ensemble_model_best.predict(X_test_normalized)
mse_ensemble = mean_squared_error(y_test, y_pred_ensemble)
print("\nMSE for ensemble model:", mse_ensemble)
```

Source: own

The obtained results of the algorithm for finding weight indicators in the proportions of reproductive cycles of different sectoral localizations at the regional level allow us to identify weight coefficients. If the algorithm shows high accuracy and corresponds to the real situation, it can be used for decision-making in the field of regional development.

3.3 Model testing

For model approbation, data for 23 years were taken for 5 regions of the Russian Federation (115 observations). The following results were obtained:

A. Weights from Lasso were obtained through L1 regularization. Weights equal to zero (0.0) mean that the corresponding indicators were excluded from the model. The best alpha value for Lasso is 0.0001. Feature weights: General economic - 0.024395; Structural - 0.024528; Socio-economic - 0.023830; Economic-demographic - 0.022412; Economic-environmental - 0.023513; Financial-economic - 0.024906. Note: In the Lasso model, the weights of the coefficients are not equal to 1 (there is no such property), the model shows the significance of each weight. Lasso penalizes large weights by shifting them towards zero and can zero some weights, which makes it useful for feature selection. The values of the weights can be normalized or unnormalized, depending on the specifics of the model and the data. If they are normalized, comparing them to each other in absolute terms is more informative than if they are not normalized.

B. Weights from Random Forest show the relative importance of each indicator for predicting the integral coefficient. The best number of trees for Random Forest: 60. The best maximum depth for Random Forest: 7. Feature weights: General economic - 0.208276; Structural - 0.199155; Socio-economic - 0.144886; Economic-demographic - 0.153327; Economic-environmental - 0.148289; Financial-economic

- 0.146066. Note: The number of trees and maximum depth are hyperparameters of the random forest model, which were determined as optimal. All weights sum up to 1. The weight of each feature shows its relative importance in the context of all the considered features.

C. Weights from Ensemble show the relative importance of each indicator in predicting the integral coefficient taking into account a combination of several models. The best number of trees for Ensemble: 85. The best maximum depth for Ensemble: 6. Feature weights: General economic - 0.204582; Structural - 0.196028; Socio-economic - 0.150484; Economic-demographic - 0.132155; Economic-environmental - 0.182629; Financial-economic - 0.134122. Note: The number of trees and maximum depth are hyperparameters for random forest and ensemble models, which were determined as optimal. All weights sum up to 1. The weight of each feature shows its relative importance in the context of all the considered features. Here it is seen that the weights are more evenly distributed among all indicators, and each of them contributes to the prediction.

D. Mean Squared Error shows the average of the squares of the errors between the real and predicted values. The smaller the MSE, the better the model predicts the data. The results obtained: MSE for Lasso: 1.3083170639779786e-07; MSE for random forest model: 0.0013299625912676495; MSE for Ensemble: 0.00136336496823814.

The smallest error is from the Lasso model, however, the Random Forest and Ensemble models provide better performance compared to linear models, as they can handle nonlinear dependencies and interactions between features, which can be particularly useful in complex integral models. At the same time, the use of linear models allows for increased interpretation of results. Among the Random Forest and Ensemble models, the Random Forest model performs the best. Figure 1 presents data on the integral coefficient by three methods (compared with average values). Note: Only some regions from the test model sample are presented.

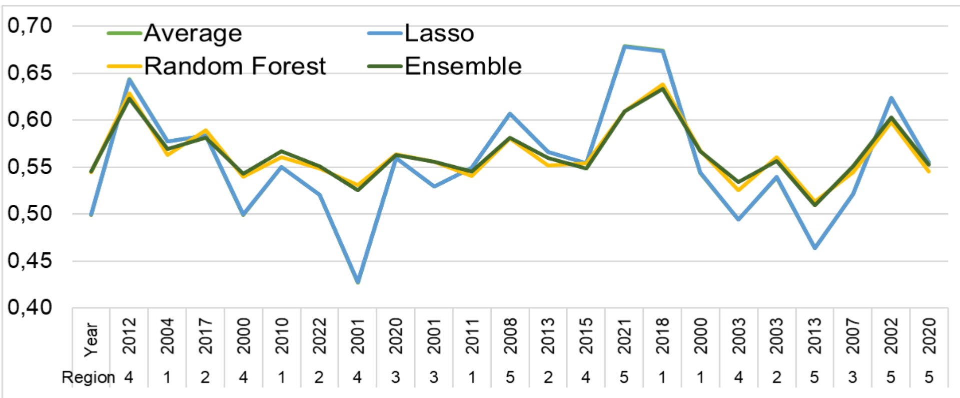

Figure 1. Comparison of the integral coefficient by three models
Source: own

3.4 Mathematical Apparatus in Regional Economics

Utilizing mathematical tools allows for accurate analysis of reproduction cycles at the regional level. Mathematical modeling can uncover hidden patterns, predict trends, and enhance management efficiency. Advanced methods like optimization and stochastic modeling help determine optimal strategies and manage risks (Duffie, 2010; Nikitin, 2010). Using spatial econometrics in regional economics enhances understanding and management by accounting for spatial correlation and diverse data. This influences the suitability of standard econometric methods (Anselin, 2013; Siebert, 2008). The mathematical framework aids in streamlining strategic thought and modeling managerial decisions. Integrating this approach in managing economic systems, especially regional management, is valuable.

To improve the forecasting system of regional development, it is acceptable to use neural network models for spatial data analysis. The advantage of neural network approaches lies in the presence of a large number of degrees of freedom that allow you to flexibly configure networks depending on a specific task, as well as offer trajectories for their further validation (Yamashkina et al., 2022). With the help of deep machine learning, it becomes possible to analyze complex social network structures to determine trends in socio-economic development by monitoring indicators characterizing the regional state of reproduction cycles (Perova et al., 2023).

When addressing methods and strategies that support new approaches to regional economics, it's worth noting the need for their adaptation to issues of effective regional development in various economic conditions (Armstrong & Taylor, 2000; Stimson et al., 2002). Using structural equation modeling and sensitivity analysis, we can evaluate the information environment and pinpoint its key elements for intellectual modeling. Digital analysis helps determine coefficients and devise systems to select these coefficients, ensuring more objective management systems and promoting economic growth (Halim, 2010; Zaytsev et al., 2022).

Effective regional planning at all decision-making levels requires detailed information about the regional economic structure. Mathematical approaches provide comprehensive analysis of the economic structure of regions (Jensen et al., 2017). In this regard, it is necessary to develop coefficients. However, large data arrays do not allow the development of models without using generalized and integral coefficients. To construct digital models and algorithms, one should also refer to a number of studies that have considered methods of mathematical evaluation and testing (Arellano, 2003; Wooldridge, 2010).

It can be concluded that new approaches to regional economics require the adaptation of methods and strategies to different economic conditions. Modelling allows us to analyze the information environment and determine key components, including weight coefficients in integral indicators.

CONCLUSION

This research has examined issues of optimizing reproductive cycles of different sector localization at the regional level using modern econometric methods. The results obtained are the development of an algorithm for finding weight indicators to determine the proportions of reproductive cycles, and the formation of mathematically substantiated integral coefficients of the state of reproductive processes. Methods of regression analysis and modeling using "Lasso", "Random Forest", and "Ensemble" were applied to construct the algorithm, allowing for effective data processing and analysis.

The results obtained have practical significance for developing a management system for reproductive processes at the regional level. Integral coefficients allow identifying the benchmark proportions of reproduction cycles in various sectors, which contributes to more rational use of resources and increases the resilience of regional economies. The proposed algorithm, implemented in the Python programming language, is an effective tool for future research and practical application in the field of optimization and management of reproductive processes.

The limitation of the research lies in the need to use available information, statistical, and analytical data. Future research in this direction will allow for the continued study of issues related to the optimization of reproduction cycles in other sectors or regions, as well as with the application of other modeling methods.

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REFERENCES

Anselin, L. (2013), Spatial Econometrics: Methods and Models, Springer Science & Business Media.

Arellano, M. (2003), Panel Data Econometrics, Oxford University Press.

Armstrong, H., Taylor, J. (2000), Regional Economics and Policy, Wiley.

Atkinson, R.D. & Ezell, S.J. (2012), Innovation Economics: The Race for Global Advantage, Yale University Press.

Babskova, O., Nadezhina, O. Zaborovskaya, O. (2019), “Innovative activities in a region in the conditions of the development of the digital environment”, International Journal of Innovative Technology and Exploring Engineering, Vol. 8, No. 12, pp. 4361–4365.
Bergstrom, J.C., Randall, A. (2016), Resource Economics: An Economic Approach to Natural Resource and Environmental Policy, Edward Elgar Publishing.
Bishop, C.M. (2006), Pattern Recognition and Machine Learning, Springer.
Breiman, L. (2001), “Random Forests”, Machine Learning, Vol. 45, pp. 5–32.
Dietterich, T.G. (2000), “Ensemble Methods in Machine Learning”, Lecture Notes in Computer Science, Vol. 1857, pp. 1–15.
Dmitriev, N., Zaytsev, A. (2021), “Intellectual Capital Management in Industry: Focusing on Superprofit”, Proceedings of the 3rd International Scientific Conference on Innovations in Digital Economy, New York, USA, pp. 97–103.
Dmitriev, N., Zaytsev, A., Faizullin, R., Bunkovsky, D. (2022), “The Instrumental Apparatus of the Innovative Potential Audit of the Enterprise in the Implementation of Project Activities”, International Journal of Technology, Vol. 13, No. 7, pp. 1484–1494.
Duffie, D. (2010), Dynamic Asset Pricing Theory, Princeton University Press, Princeton, New Jersey, USA.
Elder-Vass, D. (2016), Profit and Gift in the Digital Economy, Cambridge University Press, Cambridge, UK, https://doi.org/10.1017/CBO9781316536421.
Gall, J., Razavi, N., Van Gool, L. (2012), “An Introduction to Random Forests for Multi-class Object Detection”, Outdoor and Large-Scale Real-World Scene Analysis, Vol. 7474, pp. 243–263.
Halim, S. (2010), “Statistical analysis on the intellectual capital statement”, Journal of Intellectual Capital, Vol. 11, No. 1, pp. 61–73.
Hastie, T., Tibshirani, R., Friedman, J.H. (2001), The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Springer Science & Business Media.
Iastremska, O., Strokovych, H., Dzenis, O., Shestakova, O., Uman, T. (2019), “Investment and innovative development of industrial enterprises as the basis for the technological singularity”, Problems and Perspectives in Management, Vol. 17, No. 3, pp. 477–491.
James, G., Witten, D., Hastie, T., Tibshirani, R. (2013), An Introduction to Statistical Learning, Springer Science & Business Media.
Jensen, R.C., Mandeville, T.D., Karunaratne, N.D. (2017), Regional Economic Planning: Generation of Regional Input-Output Analysis, Routledge.
Klosterman, R.E. (1994), Regional Economics, Red Globe Press London, https://doi.org/10.1007/978-1-349-23364-9.
Konnikov, E., Konnikova, O., Rodionov, D., Yuldasheva, O. (2021), “Analyzing natural digital information in the context of market research”, Information (Switzerland), Vol. 12, No. 10, p. 387.
Lyshchikova, J., Orlova, A., Nikulina, Y., Anokhin, Y. (2016), “Regional Resources Capitalization: Theoretical and Methodological Basis”, International Journal of Economics and Financial Issues, Vol. 6, No. 4, pp. 1684–1689.
Maiti, M., Krakovich, V., Shams, S., Vukovic, D. (2020), “Resource-based model for small innovative enterprises”, Management Decision, Vol. 58, No. 8, pp. 1525–1541.
Malyshev, Y.A., Kamalova, ON. (2012), “Territorial balance of the structure of reproductive processes”, Bulletin of the Perm University, Vol. 15, No. 4, pp. 107–114.
Marshalova, A.S. & Novoselov, A.S. (1998), Fundamentals of the Theory of Regional Reproduction: Course of Lectures, Economics.
McCann, P., Ortega-Argiles, R. (2013), “Modern regional innovation policy”, Cambridge Journal of Regions, Economy and Society, Vol. 6, No. 2, pp. 187–216.
Murphy, K.P. (2012), Machine Learning: A Probabilistic Perspective, MIT Press.
Nikitin, Y.Y. (2010), “Statistical estimates of the parameters of diffusion processes”, Mathematics, Management, Computer Science, Graduate School of Management, St.Petersburg, Russia, pp. 159–194.
Nikolova, L.V., Malinin, A.M., Rodionov, D.G., Velikova, M.D. (2017), “Performance management of innovation program at an industrial enterprise: An optimisation model”, Proceedings of the 30th IBIMA Conference, Madrid, Spain, pp. 1033–1040.
de Pablos, P.O. (2020), Intellectual Capital in the Digital Economy, Intellectual Capital in the Digital Economy, 1st ed., Routledge, London, UK, https://doi.org/10.4324/9780429285882.

Perova, J.P., Grigoriev, V.P., Zhukov, D.O. (2023), “Models and methods for analyzing complex networks and social network structures”, Russian Technological Journal, Vol. 11, No. 2, pp. 33–49.
Rodionov, D.G., Konnikov, E.A., Konnikova, O.A. (2018), “Approaches to ensuring the sustainability of industrial enterprises of different technological levels”, Journal of Social Sciences Research, No. 3, pp. 277–282.
Rodionov, D.G., Pashinina, P.A., Konnikov, E.A., Konnikova, O.A. (2022), “Information Environment Quantifiers as Investment Analysis Basis”, Economies, Vol. 10, No. 10, p. 232.
Siebert, H.S. (2008), Economics of the Environment: Theory and Policy, Springer Science & Business Media.
Skousen, M. (2007), The Structure of Production, NYU Press.
Stimson, R.J., Stough, R.R., Roberts, B.H. (2002), Regional Economic Development: Analysis and Planning Strategy, Springer Berlin, Heidelberg, https://doi.org/10.1007/978-3-662-04911-2.
Tuo, S., He, H. (2021), “A Study of Multiregional Economic Correlation Analysis Based on Big Data - Taking the Regional Economy of Cities in Shaanxi Province”, Sustainability, Vol. 13, No. 9, p. 5121.
Wooldridge, J.M. (2010), Econometric Analysis of Cross Section and Panel Data, MIT Press.
Yakimenko, M.V., Zhertovskaya, E.V., Gorelova, G.V., Tkachenko, Y.G., Razvadovskaya, Y.V. (2013), Spatial and Temporal Transformation of the Reproductive Process of the Region: Cognitive Approach, Publishing House of SFU.
Yamashkina, E.O., Yamashkin, S.A., Platonova, O.V., Kovalenko, S.M. (2022), “Development of a neural network model for spatial data analysis”, Russian Technological Journal, RTU MIREA, Vol. 10, No. 5, pp. 28–37.
Zaytsev, A., Dmitriev, N., Bunkovsky, D. (2020), “Assessing the Economic Efficiency of Lean Technologies Implementation in an Industrial Enterprise”, Academy of Strategic Management Journal, Vol. 19, No. 5, pp. 1–14.
Zaytsev, A., Dmitriev, N., Bunkovsky, D., Faizullin, R. (2022), “Audit of Intellectual Capital at an Industrial Enterprise: Open Data Analysis Digital-Model”, International Journal of Technology, Vol. 13, No. 7, pp. 1473–1483.
Zhilenkova, E., Budanova, M., Bulkhov, N., Rodionov, D. (2019), “Reproduction of intellectual capital in innovative-digital economy environment”, IOP Conference Series: Materials Science and Engineering, Vol. 497, St.Petersburg, Russia, p. 012065.