Development of an Ensemble of Models for Predicting Socio-Economic Indicators of the Russian Federation using IRT-Theory and Bagging Methods

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25 November 2021

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Abstract: This article describes the application of the bagging method to build a forecast model for the socio-economic indicators of the Russian Federation. This task is one of the priorities within the framework of the Federal Project "Strategic Planning", which implies the creation of a unified decision support system capable of predicting socio-economic indicators. This paper considers the relevance of the development of forecasting models, examines and analyzes the work of researchers on this topic.

The authors carried out computational experiments for 40 indicators of the socio-economic sphere of the Russian Federation. For each indicator, a linear multiple regression equation was constructed. For the constructed equations, verification was carried out and indicators with the worst accuracy and quality of the forecast were selected. For these indicators, neural network modeling was carried out. Multilayer perceptrons were chosen as the architecture of neural networks. Next, an analysis of the accuracy and quality of neural network models was carried out. Indicators that could not be predicted with a sufficient level of accuracy were selected for the bagging procedure. Bagging was used for weighted averaging of prediction results for neural networks of various configurations. Item Response Theory (IRT) elements were used to determine the weights of the models.

Keywords: Socio-economic Indicators of the Russian Federation, Forecasting, Bagging, Multiple Linear Regression, Neural Networks, Item Response Theory.

Acknowledgement: This research was performed in the framework of the state task in the field of scientific activity of the Ministry of Science and Higher Education of the Russian Federation, project "Development of the methodology and a software platform for the construction of digital twins, intellectual analysis and forecast of complex economic systems", grant no. FSSW-2020-0008.

1. Introduction

One of the most priority tasks of the modern state is the digital transformation of key processes. In Russia, to solve this problem, the National Program "Digital Economy of the Russian Federation" was developed, within the framework of which federal projects are being implemented. One of these projects is the project "Digital Public Administration". The main objective of this project is the introduction of digital technologies and platform solutions in the areas of public administration and the provision of public services, including services in the interests of the population, small and medium-sized businesses and individual entrepreneurs (see https://data-economy.ru/government). Within the framework of the project, one of the directions concerns the solution of the problem of information support for strategic planning. This direction is being investigated within the framework of the Digital Strategic Planning project (see https://www.economy.gov.ru/material/directions/strateg_planirovanie/cifrovoe_stratplanirovanie). The purpose of Digital Strategic Planning is to develop a management decision support platform at all levels of government. One of the functions of such a platform is the ability to analyze statistical data in order to monitor and predict key economic indicators.

The indicators of the Russian economy can be roughly divided into two classes. The first includes those indicators that can be predicted by classical models of statistics and econometrics. The second class includes indicators that have structural breaks and are not predicted using classical models, and therefore it is necessary to apply more complex machine learning models. However, intelligent models also do not always allow to obtain an adequate forecast result for some of these indicators. In this regard, an approach that allows not only using econometric methods in conjunction with intellectual ones, but also improving the results obtained using a predictive ensemble of models is relevant.

The aim of this study is to develop an ensemble of forecasting models based on several configurations of direct propagation neural networks, combined into an ensemble using the bagging method, supplemented by the IRT (item response theory) technique. The main ideas of the IRT theory were applied in the study to assess the contribution of the result of each model to obtain the most accurate prediction. This approach was used for the first time and has not been published anywhere before.

As a result of computer experiments, multiple linear regression equations were constructed for 40 socio-economic indicators of the Russian Federation. However, for 23 of them it was not possible to obtain reliable and high-quality results. Methods of neural network modeling were applied to these indicators. For each of the 23 indicators, multilayer perceptrons of various configurations were constructed. Further, based on the probabilities (weights) obtained on the basis of the IRT theory, the averaged forecasts were calculated using the bagging method. The mean relative error (MAPE) was used as a metric for assessing the forecast accuracy. As a result, it was possible to increase the forecasting accuracy for all indicators by an average of 20%.

The theoretical significance of this study lies in the formation of a new forecasting method, previously not used for forecasting, which makes it possible to increase the forecasting efficiency of key indicators of the Russian economy. The practical significance of the study lies in conducting a large-scale computer experiment, which made it possible to prove the feasibility of using the presented method in the tasks of making forecasts in the field of economics.

Within the framework of this article, the following sections are described:

- The Literature Review presents the results published by leading scientists in the field of the application of ensembles of models for forecasting.
- The Methodology section describes in detail the methodology developed by the team of authors, as well as describes in detail the parameters of the developed models and teaching methods.
- The Results section describes the results of the obtained calculations and the verification of the models.
- The Discussion section includes promising directions for the development of the presented research.

At the end of the article, Conclusions section is presented, including a description of the main results of this study, as well as a list of references.

2. Literature Review

Modern researchers working in various subject areas often use bagging techniques to predict time series.

Work (Awajan et al., 2017) is devoted to the construction of an ensemble of models based on empirical mode decomposition (EMD), quantile regression (QR) and Holt-Winter model (HW). These models are combined into an ensemble using bagging methods.

In the article (Kadir Özen et al., 2021), the authors forecast electricity prices in various markets and aggregate the forecasts using bagging methods.

The authors of (Huanhe Dong et al., 2021) consider the classical application of an ensemble of models based on regression decision trees combined into an ensemble using a bagging algorithm in order to predict short time series.

In (Xiang Wang et al., 2021), the problem of predicting the movement of tropical cyclones using regular extreme learning machines and the bagging method is highlighted.

Within the framework of the article (Bergmeir et al., 2016), the application of bagging methods to the construction of time series forecasts based on exponential smoothing is considered.

The authors of the article (Jung Seungwon et al., 2020) carried out research in the field of forecasting based on neural networks combined into a single predictive ensemble of models using bagging methods.

Forecasting the amount of generated solar electricity is discussed in (Choi Sunghyeon et al., 2020). As part of the article, the authors applied models such as random forests, XGBoost and LightGBM, as well as retro data. Based on these models, an ensemble was developed using bagging methods.

Article (Athanasopoulos et al., 2017) includes research on tourism demand forecasting based on bagging applied to regression models.

In (Jin Sainan et al., 2014), calculations are given using the bagging algorithm to linear models for forecasting time series. This approach has improved the predictive power of linear models.

Work (Zarate Perez Eliseo et al., 2020) includes the construction of a forecasting model for power generation using an ensemble based on neural networks and bagging. Within the framework of this work, a method is used for constructing an ensemble of models based on artificial neural networks of direct propagation (perceptrons), combined using a bagging algorithm. However, unlike all the presented articles, it is proposed to improve this method using elements of the IRT theory to determine the measure of the contribution of each neural network model to the average forecast.

3. Methodology

Researchers of the Plekhanov Russian University of Economics developed a hybrid approach to scenario forecasting based on multiple linear regression models and intelligent methods [Kitova O.V et al., 2016]. This hybrid approach became the basis for the development of the analytical forecasting system "Horizon" [Kitova O.V et al., 2020]. Within the framework of this system, it is possible to build ensembles of models based on the hybrid approach using gradient boosting as an instrument to aggregate forecasts (Kitova, Dyakonova, Savinova, 2020)

Within the framework of this work, forecasting of the indicators of macroeconomics and the social sphere of the Russian Federation was carried out. As a data source, we used official statistics published in the Unified Interdepartmental Information and Statistical System (https://www.fedstat.ru/) and on the official website of the Federal State Statistics Service ((https://rosstat.gov.ru/).

At the first stage, forecasting was carried out using multiple linear regression models. Then, the models were verified using indicators: the coefficient of determination (R2), the Durbin-Watson test (DW), and Fisher's statistics (F). The average relative error (MAPE) is calculated as an estimate of the accuracy. According to the results of verification, the indicator models were divided into classes: with high accuracy and quality of the forecast, medium accuracy and high quality, low accuracy and high quality, high accuracy and low quality, medium accuracy and low quality and low accuracy and quality. To carry out this classification, the boundary values of the verification indicators were expertly established (Table 1).

Table 1.

Values of Accuracy and Quality Criteria for Forecasts

Quality assessment settings

coefficient of determination (R^2),	> 0,4
values of Fisher statistics (F-stat)	> 5,0
The Durbin-Watson criterion (DW)	0,8 < DW< 3,2

Accuracy estimation settings (Δ)

High	Middle	Low
<0,06	0,06< Δ <0,16	>0,16

To predict indicators for which it was not possible to obtain acceptable results using multiple linear regression, models of artificial neural networks were built.

In the framework of this study, a multilayer perceptron was chosen as the architecture of neural networks. Back propagation was chosen as the training method. For each indicator, several neural networks of various configurations and training parameters were built. Experimentally, the most effective models of neural networks were selected, the parameters of which are presented in Table 2.

Table 2.

Neural network parameters

Number of neurons on the hidden layer	Number of learning epochs	Activation function
15, 20, 25, 30	60, 100	RELU, ELU, Sigmoid

Thus, for each indicator, 32 neural network configurations were built. The MAPE metric is used to determine the prediction accuracy of neural networks. The quality is determined by the values of the learning errors.

At the next stage, for indicators that could not be predicted using neural networks with sufficient forecast accuracy, an ensemble of predictive models was built, averaging the results of the constructed neural networks using bagging.

Bootstrap aggregating is one of the most modern and popular methods for building model ensembles.

Within the framework of the bagging method, the following stages of constructing a predictive ensemble of models are performed:

1. Selection of training data;
2. Building several forecasting models based on one or more machine learning methods;
3. Weighted averaging of the predicted values of the constructed models, taking into account the predictive power of each of them.

Thus, the ensemble looks like this:

$$\alpha(x) = \sum_{i=1}^{n} w_i * \beta_i(x) \qquad (1),$$

where α (x) is the voting result

β (x) - results of basic algorithms

w - are the weights of the algorithms.

This method of building ensembles requires assigning weights to each of the predictive models. IRT elements were used to assign weights to the models.

Item Response Theory (IRT) is a set of methods for constructing, analyzing tests and evaluating their results based on specified statistical models. IRT is designed to evaluate the latent parameters of subjects and test tasks based on mathematical and statistical measurement models and is part of a more general theory of latent structural analysis (LSA), although each of these areas has its own characteristic features and its own scope. In practice, the inverse problem is always stated: according to the responses of the subjects to the test items, estimate the values of the unknown parameter θi (i = 1, 2, ..., N), which determines the level of training of N subjects, depending on the parameter δj (j = 1, 2, .., M), which determines the difficulty of each of the M test items (Steven P. Reise et al., 2015).

When applying this theory in assessing respondents' answers, the following formulas are used:

$$\theta = \ln\left(\frac{K}{M-K}\right) \qquad (2)$$

$$\delta = \ln\left(\frac{N-T}{T}\right) \qquad (3)$$

where T is the number of respondents who solved the task correctly,

K is the number of tasks solved correctly by the respondent,

N is the number of respondents,

M is the number of tasks.

In this study, the IRT technique was taken and transformed to rank the forecasting models and assign them weights for the bagging procedure. This transformation is shown in Table 3.

Table 3.

Redefining the meaning of model parameters

Parameter of the IRT model	In education	In the "Horizon" system
θ	Latent level of knowledge	Latent level of the model's ability to explain/predict indicators
δ	Latent level of difficulty of an item (task)	Latent level of complexity of an item (indicator)

Formulas for estimating the parameters of IRT models also have a physical meaning, which should be redefined within the framework of a new subject area. Therefore, it is also necessary to redefine the variables included in the parameter calculation formulas.

Table 4.

Redefining the meaning of model parameters

Variable	In education	In the "Horizon" system
N	Number of respondents	Number of models = 32
M	Number of tasks	Number of indicators = 23
T	The number of respondents who solved the task correctly	Sum of generalized accuracy values for multiple models
K	The number of tasks solved correctly by the respondent	The sum of the values of the generalized accuracy for the set of predicted indicators

Thus, the calculation within the framework of this study consisted of the following stages:

1. Construction of multiple linear regression models;

2. Model verification and selection of models with poor values of accuracy and quality of regression models

3. Plotting direct propagation neural networks for each indicator with low values of accuracy and quality

4. For the indicators for which it was not possible to obtain an acceptable result of forecast accuracy using neural networks, a bagging procedure was carried out.

4. Results

At the first stage, multiple linear regression models were calculated. The result of verification of the obtained equations is presented in Table 5.

Table 5.

The result of verification of linear regression models

Verification		Accuracy criterion		
		High	**Middle**	**Low**
Quality criteria	**High**	12	5	2
	Low	6	6	9

For 9 indicators with low accuracy and quality of the forecast, neural network models were built. As a result, using neural networks, it was possible to improve the forecast for 4 indicators (table 6).

Table 6.

The result of verification of neural network models

Verification		Accuracy criterion		
		High	**Middle**	**Low**
Quality criteria	**High**	18	8	0
	Low	6	6	2

However, the forecast for 2 indicators could not be improved using neural networks. For these indicators, the bagging method was applied (results see in Table 7).

Table 7.

The results of verification of neural network and bagging models

Indicator	MAPE of the best neural network model	R2 of the best neural network model	MAPE of the bagging model	R2 of the bagging model
Unemployed people registered with state employment agencies, thousand people	0,56	0,9	0,12	0,9
Natural population growth (decline), per thousand people	0,23	0,9	0,11	0,9

Thus, the use of the bagging method has improved the accuracy for indicators that could not be predicted using an artificial neural network.

5. Discussion

As part of this work, the socio-economic indicators of the Russian Federation were predicted using an ensemble of models based on multiple linear regression, neural networks, and also using the bagging method.

In the future, it is planned to carry out computations using various machine learning methods (regression decision trees, vector regression method, etc.), combined into predictive ensembles of models. In the future, additional computational experiments will be carried out for indicators from various spheres of the Russian economy.

6. Conclusion

Currently, the relevance of building reliable forecasting models is increasing, which would improve the quality of decisions made at the strategic level. The task of developing such models is one of the tasks of the Strategic Planning project, which is one of the federal projects of the Digital Economy of the Russian Federation national project. Within the framework of this study, computational experiments were carried out to forecast one of the key indicators of the socio-economic sphere of the Russian Federation.

The authors have implemented the following steps:

1. Collected data on 40 socio-economic indicators of the Russian Federation;
2. Conducted the construction of a system of equations of multiple linear regression;

3. Constructed 23 configurations of neural networks for each indicator with low accuracy and quality.
4. A bagging model was built using elements of the IRT methodology for indicators for which the forecasts could not be improved using artificial neural networks.

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