AMERICAN JOURNALS
Open Access, Peer Reviewed Journals
American Journal of Business Management, Economics and Banking
ISSN (E): 2832-8078 Volume 20, | January, 2024

USE OF MACHINE LEARNING METHODS IN FORECASTING INDICATORS OF FISCAL AND MONETARY POLICY COORDINATION FOR THE ECONOMY OF UZBEKISTAN

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A B S T R A C T	K E Y W O R D S
This paper proposes a new type of solution for Uzbekistan economy using several machine learning methods: LASSO, Ridge, Random Forest, Gradient Boosting and Artificial Neural Networks. This paper is one of the first attempts to apply machine learning methods to the macroeconomic forecasting in Uzbekistan. The main result of this paper is the confirmation of the possibility of more accurate forecasting of economic indicators in Uzbekistan using machine learning methods.	Macroeconomic indicators, ARMA, RMSE, LASSO, economic activity, random forest.

Introduction

This can be explained by the fact that there is a large number of works on forecasting various macroeconomic indicators among economists. Econometrics, a separate branch of economics that deals with such economic forecasts, has developed its own traditional methods for the development of these forecasts. With the help of these methods, various indicators of the economy can be efficiently and accurately forecasted. By the beginning of the 21st century, in economic forecasting, together with econometric models, the practice of forecasting with the help of computer - artificial intelligence began. Such methods of forecasting through artificial intelligence are called “machine learning” in a broad sense.

“Machine learning” is one of the hottest topics today. Although terms such as “artificial intelligence” (AI) and “Big Data”, which are constantly heard in various literature and news, are considered as technologies of the distant future, their true meaning is much closer to everyday life. Currently, machine learning is used in various fields. In particular, it is used to filter e-mail as spam, to recommend the necessary services and goods to the user, to forecast future demand, and even in autonomous (self-driving) cars. In a broad sense, it can be said that machine learning is the determination of the computer's future actions based on current data without specific programs. Autonomous machines work in this way: the machine receives information from its surroundings, analyzes them and makes further decisions based on this information. There are many ML algorithms for performing these tasks.

Currently, the issue of correct forecasting of macroeconomic indicators is one of the problems faced by economists all over the world. This problem is also actual for the economy of Uzbekistan, and great attention is being paid to forecasting these indicators.
The use of ML (machine learning) methods in forecasting macro indicators has been used since the beginning of the 21st century, and these methods are several times superior to traditional econometric models.
The purpose of this work is to apply the use of ML methods in the forecasting of macroeconomic indicators for the economy of Uzbekistan. Despite the fact that these methods have become the subject of research for economists all over the world, the author did not find any scientific works showing their application in Uzbekistan.
The scientific importance of this topic is based not only on the fact that it is an absolutely new topic for the economy of Uzbekistan, but also on the fact that the issue of using ML methods for forecasting time series in the economy is one of the interesting topics for economists all over the world. In general, in world practice, this topic began to be covered only at the beginning of 2000s, while the period of coverage of some models covered in the work goes back to 2010s. That is, the history of this topic is not so long and the topic has not been studied enough during this period.

II. LITERATURE REVIEW

Many scientific works of foreign researchers have been written on the topic of using machine learning methods in forecasting macroeconomic indicators. The research of Stock and Watson (2008) is devoted to inflation forecasting, and *Stock and Watson* (2008) divide and analyze different models into four main groups [1]. The first group is based on the use of only inflation time series: ARMA, RW and the authors' own unobserved components and stochastic volatility model (Unobserved Components - Stochastic Volatility, UC-SV) models are included. The second group includes models whose variables are economic activity, such as unemployment and interruptions in production. The third models are based on surveys of professional forecasters. The fourth group includes models that do not have variables not included in the second group. The models make pseudo-real time forecasts for a 10-year period based on quarterly data. Root Mean Square Error (RMSE) is used to evaluate the model. The conclusion was that models using only time series of inflation do not lag behind multivariable models. Taking into account the difficulties in creating multivariable models, the authors conclude that univariate models are preferable.
The article by *Faust and Wright* (2013) is also devoted to inflation forecasting [2]. The authors compare 17 different ML models. Among them - "Random Walk", autoregression methods (AR (1) and AR (p)), a model based on the Phillips curve, structured vector autoregression (SVAR), Bayesian averages model (BMA)), there is a dynamic stochastic model of general equilibrium (Dynamic Stochastic General Equilibrium, DSGE) and others. The authors evaluate the models using root mean square deviation (RMSE). In this case, the AR (1) model is taken as a benchmark, and all models are evaluated against this model. The model based on the opinion of professional forecasters wins as the best model. However, this study also proved that the best multi-factor models of the above study do not outperform the best one-factor models.
Russian researchers *Fokin and Polbin* (2019) use the VAR-LASSO model in the forecast of macroeconomic indicators and make forecasts for the Russian economy for 2019-2024 [3]. They compare VAR-LASSO model with BVAR (Bayesian Vector Autoregression), VAR, ARIMA

methods and show the superiority of their model. Their pseudo-real-time forecasts for 2016-2018 use the RMSE (root mean square deviation) indicator in comparison with the forecasts of the Russian Ministry of Economic Development and the International Monetary Fund. The peculiarity of this work is that they can add the slowdown of the Russian economy to the model as a structural change, thereby increasing the accuracy of the model.

Generally speaking, the use of machine learning methods in forecasting macroeconomic indicators is an urgent issue not only for the economy of Uzbekistan, but also for the economy of developed countries. Due to this, the number of scientific articles on this topic is increasing rapidly.

III. DATA AND METHODOLOGY.

1. Regularization models

We have discussed above what is the biggest problem of the models created for forecasting - although the model shows a low error result within the sample, it is not suitable for forecasting outside the sample. This problem is called "overfitting". That is, the model excessively "reads" on the basis of assimilation of information that is specific to the data it sees in the sample, but is not available in general economic processes. Theoretically, it is possible to create a model that reduces the sampling error to less than 1%, but the question of using this model in forecasting remains open.

To solve this problem, a regularizer is added to the simple linear regression equation, which regulates the excessive "learning" of the model. In a general sense, this regularizer has the following formula [4]:

$$R(x) = \gamma \sum_{i=1}^{q} |x_i| + (1-\gamma) \sum_{i=1}^{q} x_i^2 \tag{1}$$

where, R(x) is a linear regression equation, $\gamma \in [0;1]$, q is the number of x parameters. When $\gamma \in (0;1)$ is in the above regularizer, this model is called Elastic Net. In case $\gamma = 1$, this model is called *LASSO* (*Least Absolute Shrinkage and Selection Operator*). The case where $\gamma = 0$ is called *Ridge regression*.

Their equations can be shown as follows [5]:

$$y(\hat{\beta}) = \underbrace{\sum_{i=1}^{n} \left(Y - X\hat{\beta}\right)^2}_{\text{Sum of squares}} + \underbrace{\lambda \sum_{j=1}^{p} \left|\hat{\beta}_j\right|}_{\text{LASSO penalty}} \rightarrow min \tag{2}$$

The above formula is the formula for LASSO regression.

Although ridge regression is similar to LASSO, it is slightly different from it [6].

$$\hat{\beta} = \sum_{i=1}^{n} \left(Y - X\hat{\beta}\right)^2 + \lambda \sum_{j=1}^{p} (\hat{\beta}_j)^2 \rightarrow min \tag{3}$$

The Elastic Net model is created by adding the above two models [7]:

$$\hat{\beta} = \sum_{i=1}^{n} \left(Y - X\hat{\beta}\right)^2 + \lambda \sum_{j=1}^{p} \left[(1-\alpha)\left(\hat{\beta}_j\right)^2 + \alpha\left|\hat{\beta}_j\right|\right] \rightarrow min \tag{10}$$

Through the regularizer λ in the equation, a special "penalty" is applied when the model deviates from the general laws and adapts to the selection. There are several methods of choosing this penalty factor. First, Akaike and Bayesian information criteria (AIC and BIC) or cross-validation, widely used in ML, are used.

The main difference between LASSO and ridge regression is based on the fact that the possibility of "penalizing" the parameters of the equation is different. In LASSO regression, indicators with a low level of statistical significance can be completely excluded from the model, and in ridge, even if their parameters are reduced, they will never be equal to zero.

2. Machine learning methods

The decision tree method[1], which is considered one of the pure ML methods, is mainly used in classification problems (that is, grouping different indicators according to their sign), but the method is also used for regression. Based on the elements of graph theory, the decision tree divides the selection into two or more parts at each stage based on certain criteria.

Decision trees have several serious drawbacks, including the above-mentioned "overfitting" problem of the model. Theoretically, it is possible to build a decision tree in such a way that there is no error at all in the sample data. To prevent this problem, the depth of the tree, that is, the maximum number of its "branches", is determined. The second way to deal with overfitting is to create an "ensemble" from several decision trees.

Ensemble methods are one of the most important parts of ML. Usually, ensemble methods are weighted according to the accuracy of other methods and determine their average. This eliminates the problem of overfitting and allows to increase the level of accuracy of the model.

Random Forest (RF) - allows you to create an ensemble from different decision trees [8]. The RF model builds decision trees based on data randomly selected from the sample. The number of decision trees in RF can be unlimited. Although the increase in their number increases the accuracy of the model, it also increases the time for calculation. Each decision tree is checked for accuracy on data outside of the random sample. More specific trees are given greater weight and average values from all of them are considered correct.

Boosting - is another ensemble method, although it can be built from any family of models, in this work, busting is built from decision trees [9]. The difference between the busting method and the random forest is that the decision trees are not built independently of each other, instead, each decision tree is built taking into account the errors of the previous model.

The structure of boosting is as follows [10]:

1. An initial decision tree is constructed over the entire sample. Its main task is to reduce the difference between the constructed model and real indicators.

$$b_1(x) = \sum_{i=1}^{m}\left(y_i - b(x)\right)^2 \to min \tag{4}$$

2. The result of the first step is taken as a base model:

$$B_1(x) = b_1(x) \tag{5}$$

3. Based on the basic model, errors are calculated:

$$e_i^1 = y_i - B_1(x) \tag{6}$$

4. The second model is created taking into account these errors:

$$b_2(x) = \sum_{i=1}^{m}(b(x_i) - e_i^1)^2 \to min \tag{7}$$

5. The new result is added to the previously obtained base model with a certain coefficient $\gamma \in (0;1]$. In this work, the value $\gamma = 0{,}2$ was obtained. It is important to choose its value correctly. The new model looks like this will have:

[1] Note: in some sources it is also translated as "solution tree".

$$B_2(x) = B_1(x) + \gamma b_2(x) \quad (8)$$

6. This sequence of operations is repeated up to a predetermined n value, and the final model will look like this:

$$B_n(x) = \sum_{i=1}^{n} \gamma^{i-1} b_i(x) \quad (9)$$

The higher the number of iterations n in the busting model, the higher the accuracy of the model.

Artificial neural networks - are considered one of the first ML methods and try to replicate the learning of the human brain. In its simplified version, the given information is transmitted through neurons and is based on achieving the final result [11]. The transfer of x_1, x_2 and x_3 in the simplest form through neural networks can be seen in the picture below.

In this case, the vertices of the graph are called "neurons". These neurons work like neurons in the human brain - information is transmitted between them. Unlike simple econometric models, neural networks do not depend on predetermined patterns. On the contrary, artificial neural networks can be compared to a small child - the model also learns step by step. For this, one indicator is taken as the main benchmark. In our model, the mean square deviation is the basis for learning the model. That is, the model tries to reduce the degree of deviation by transferring different quantities from the neurons.

The parts of neural networks between the input point and the final output are called “layers”. The higher the number of these layers, the higher the level of accuracy. But this complicates the calculation process.

IV. ANALYSIS AND RESULTS

The necessary information for forecasting macroeconomic indicators has a monthly, quarterly and annual frequency. In this case, if the inflation calculated by the consumer price index and the exchange rate of the UZS against the US dollar consists of monthly data from January 2000 to December 2019, GDP, unemployment rate, Central Bank refinancing rate, in a broad sense, the money supply, the real interest rate consists of data collected at annual and quarterly intervals.

Table 1 Data used in the model[2]

Variable	Unit of measure	Designation	Source
Gross domestic product (at current prices)	billion soums	*GDP*	State Statistics Committee
Consumer price index	%	*CPI*	State Statistics Committee
Unemployment	%	*Unemployment*	2009-2019: DSQ, 2000-2009: TradingEconomics.com
GDP deflator	%	*Deflator*	Asian Development Bank
Money supply	billion soum	*M2*	Asian Development Bank
Foreign trade balance	million dollars	*ForTrade*	2000-2015: OTB, 2016-2019: DSQ
The exchange rate of the US dollar against the soum[3]	soum	*USD*	norma.uz
Average salary	soum	*Wage*	State Statistics Committee

[2] Note: These indicators were used in the model in logarithmic form
[3] Note: To eliminate the effect of devaluation, the data until September 2017 was doubled. This soum was considered close to the market rate at that time

These data were used to construct multivariable models, including ML methods. The data in Table 1 were selected for their high importance in the model.

Data processing is one of the most important issues in improving the accuracy of the model. In this case, the main method is to bring non-stationary (non-permanent) data into a stationary (permanent) form. The fact that economic processes do not change their characteristics over time is classified as a state of stationarity. In econometrics, data stationarity means that their average and dispersion indicators do not change.

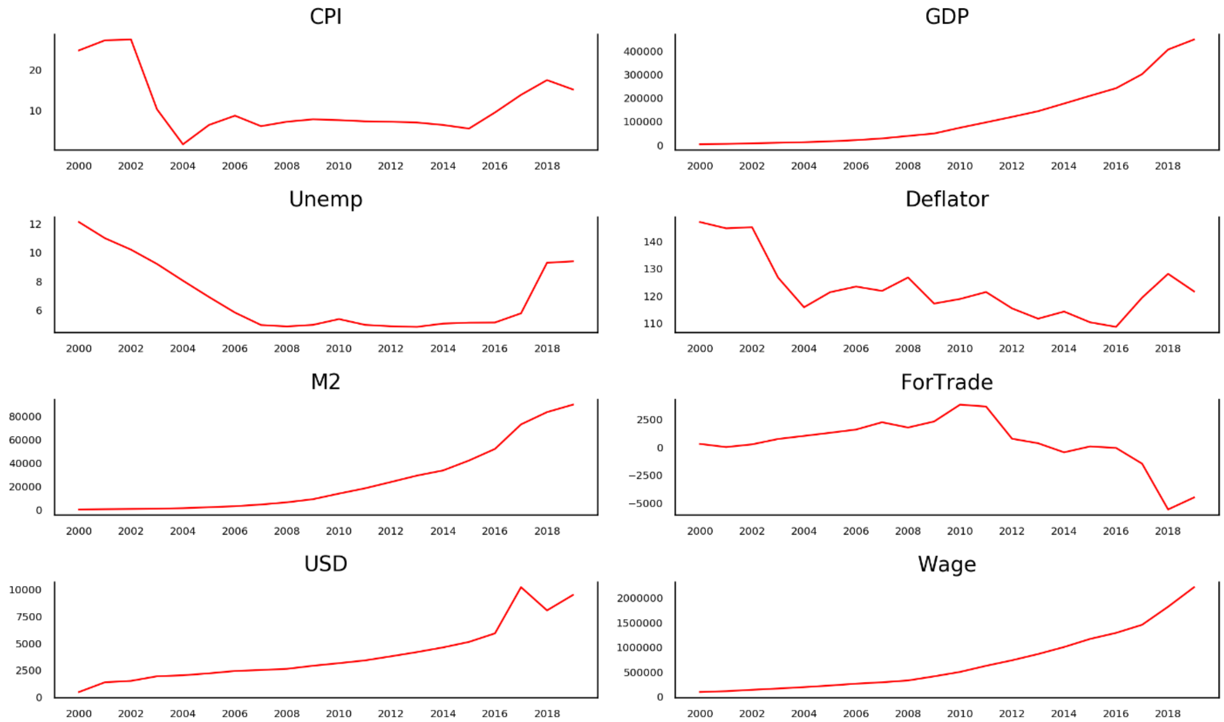

Figure 1. Dynamics of change of the main macroeconomic indicators[4].

Figure 1 shows the dynamics of the main macroeconomic indicators. Their dynamics will change until these data are brought to a stationary state for the purpose of forecasting.

The OLS (method of least squares) model was chosen as a benchmark model among econometric models for forecasting the GDP growth rate, that is, a model used to compare the accuracy of other models.

Table 2 Evaluation of GDP growth rate forecasting models[5]

Indicator	Boosting	Random Forest	Lasso	Ridge	VAR	OLS
MAE	0.5	1.41	1.61	1.79	2.38	3.64
MSE	0.367	2.16	4.427	3.825	6.073	17.168
Accuracy%	91.10%	72.92%	71.12%	67.61%	56.40%	32.40%

[4] Author development
[5] Formed by the author

In assessing the accuracy of GDP growth rate forecasting models, the indicators of the last four years (2016-2019) were evaluated. ML models - Boosting and Random Forest outperform traditional econometric models by all indicators of accuracy assessment.
Among the linear models, the Lasso model shows higher accuracy than ordinary least squares and Ridge regression. Ridge regression outperforms Lasso only in terms of MSE. Given the larger "penalty" of MSE for larger errors, Lasso has difficulty estimating unexpected changes. Another peculiarity of lasso - the ability to select variables was achieved in this process. Lasso chose to leave only 6 out of 8 variables in the model.

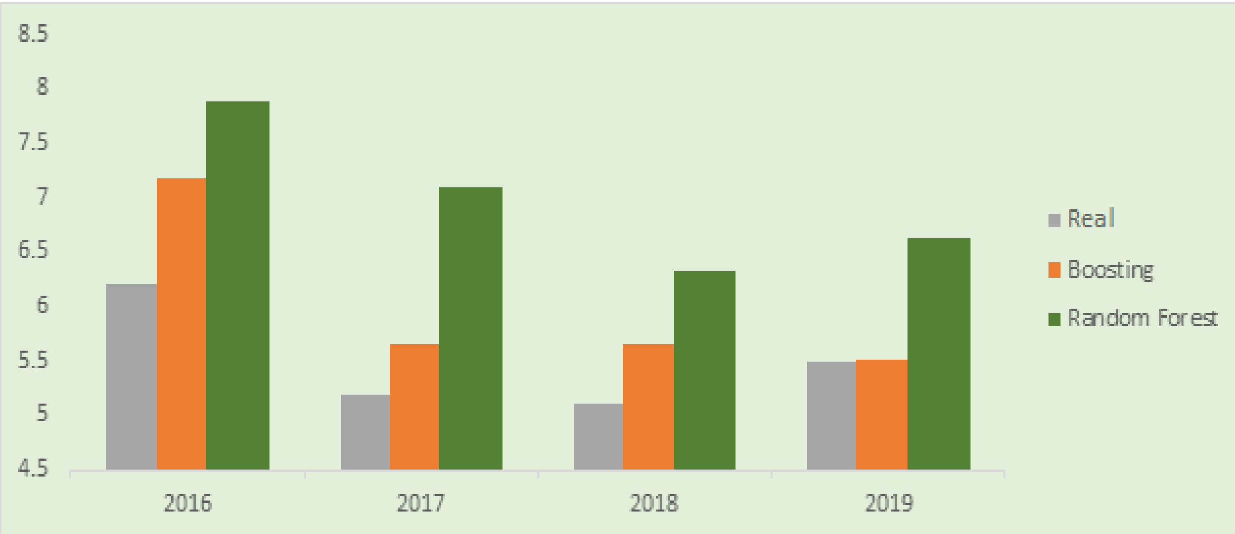

Figure 2. Comparison of Boosting and Random Forest model forecasts with real indicators[6]

The Boosting and RF models generally put their predictions slightly higher than the actual figures. The average boosting model is wrong by 0.5 percentage points (MAE=0.5). It is worth noting that the forecasts for 2019 are equal to the actual indicators.

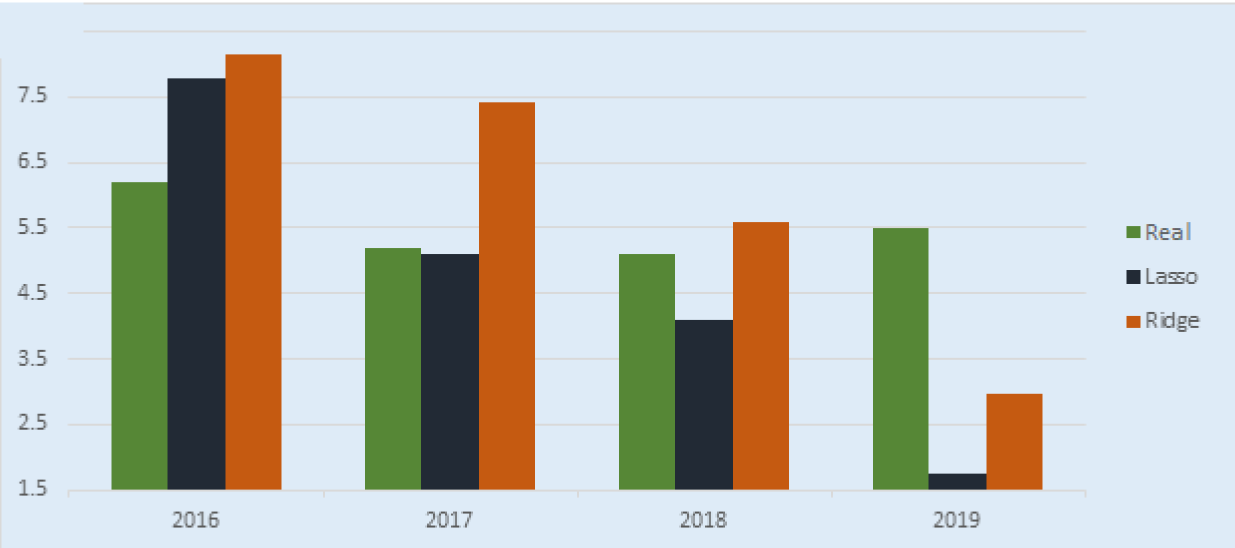

Figure 3. Comparison of lasso and ridge regression forecasts to actual indicators[7]

[6] Formed by the author
[7] Formed by the author

Comparing the lasso and ridge regression forecasts with the actual figures, it can be seen that the models are on average 1.61 and 1.79 percentage points wrong each year, respectively. One of the reasons for recording such an indicator is that in 2019, both models abnormally predicted the economic growth indicator at a much lower level than the actual one. Because of this, it negatively affected the accuracy of the models.

When creating the VAR model, lags of indicators 1 year ago were taken into account. In this case, the main reason is that economic indicators do not immediately affect the GDP growth rate. The fact that the VAR (1) model did not show such a good result is explained by the extreme sensitivity of this model to the quality of data. Some deficiencies in the quality of data generated for the economy of Uzbekistan directly affected the quality of the model.

V. CONCLUSIONS AND SUGGESTIONS

Machine learning methods, which are now popular all over the world, are showing themselves in a positive way in forecasting the indicators of Uzbekistan's economy. The following conclusions are drawn from this work:

1. Random Forest and Boosting methods demonstrate the extent to which machine learning can be used in economic sectors today. Although these models were not originally created for modeling time series, their flexibility, i.e. universality, for every field shows that they can be used in the forecast of macroeconomic indicators.
2. Even if the application of neural networks did not give a satisfactory result in the forecast of the level of inflation in Uzbekistan, the potential of this model is great. Taking into account the fact that thousands of articles in various publications are devoted to this topic every year in the international scientific community, the implementation of neural networks and, in a broad sense, “deep learning” algorithms becomes one of the most urgent issues. The current unsatisfactory results are explained by the insufficient number of observations for the algorithm, the author's insufficient knowledge and experience in the field, and the unavailability of calculation capabilities.

Generally speaking, the application of machine learning in various areas of the economy is one of the important parts of the fourth industrial revolution, the “digital economy”, which are currently current topics. Researching the issues of applying these methods for the economy of Uzbekistan will help to increase the competitiveness of the country's economy, to adapt to the changes of the new era more quickly, and to increase the accuracy of future forecasts.

Based on these results, the following conclusions are drawn regarding the improvement of the forecasting accuracy of macroeconomic indicators, in particular, inflation rates calculated through the consumer price index in Uzbekistan:

• consider the issue of using machine learning methods in forecasting;
• implementation of foreign experience in the use of artificial neural network methods in the economy of Uzbekistan;

By applying these recommendations, Uzbekistan will have the opportunity to increase the accuracy of forecasting macroeconomic indicators and quickly respond to various economic processes.

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