Economic Cycle Prediction using Machine Learning – Russia Case Study*

B.K. Amos, I.V. Smirnov, I.A. Aidrous, R.R. Asmyatullin, S.G. Glavina

Peoples Friendship University of Russia (RUDN Universiry), Moscow, Russia

Abstract. The long-term development of the world economy is characterized by cyclical development. To date, there is no single accepted approach to describe the nature of the economic cycle. Therefore, studies of economic and political cycles are one of the key areas of economic theory. Econometrics and machine learning have a common goal: to build a predictive model, for a target variable, using explanatory variables. This research aims to identify economic cycle in Russian Federation using collective factors. It uses a different approach, concerning classical econometric techniques, and shows how machine learning (ML) techniques can improve the accuracy of forecasts. We used three machine learning algorithms such as k-Nearest Neighbors (kNN), Random Forests (RF) and Support vector machines (SVM). The research is based on 30 economic factors for the period 1990-2020 from FRED, World Bank, WTO, Federal State Statistics Service, Bank of Russia etc. The results indicate that the Russian economy would be very active (peak) in the next quarters. This result could be a new approach to provide policy recommendations to authorities and financial institutions in particular.

Keywords: *macroeconomics, Machine Learning, Econometric Forecasting, Russian economy, Economic cycle.*

DOI: 10.14357/20790279230112

Introduction

One of the most important characteristics of a developed market economy is its cyclical development - periodic ups and downs in business activity. Economic cyclicality can be traced in the change in the main macroeconomic indicators – the volume of real GDP, the intensity of investment, the unemployment rate, etc.

The cyclical nature was influenced by the deepening of the integration and liberalization processes; strengthening the international division of labor; mass

Application and rapid development of information and communication technologies, software, nanotechnology, composite materials. Digitalization of the economy and covid-19 crisis in the last few years have played an important role in the emergence of many other services and activities: e-commerce, remote exchange trading, mobile banking and others creating tons of information to manage hence big data.

The current forecasting literature has focused on matching specific variables and horizons with a particularly successful algorithm. The intersection of machine learning (ml) with econometrics has become an important research land- scape in economics. Machine learning has gained prominence due to the availability of large data sets, especially in microeconomic applications (coulombe et el., 2020). De- spite the growing interest in ml, understanding the properties of ml procedures when they are applied to predict macroeconomic outcomes remains a difficult challenge.

There are many techniques and methods to analyze and process this information. Machine learning lies at the intersection of mathematics and statistics, computer science and big data. Simply put, machine learning is a way to put big data analysis into service. With the help of such technology, the computer can learn to identify certain patterns, to "meet", with which it will perform certain actions - buying or selling stocks, segmenting potentially high-yielding customers, or identifying faulty products on the conveyor belt.

Econometrics and machine learning share a common goal, namely the construction of a predictive model, for a variable of interest, using explanatory variables (or features). However, these two approaches have developed in parallel, creating two different cultures. The first aims to build probabilistic models to de-

* This paper has been supported by the RUDN University Strategic Academic Leadership.

scribe economic phenomena. The second uses algorithms that learn from their errors, for the purpose of prediction or classification. Recently, learning models have proven to be more efficient than traditional econometric techniques and are able to handle much larger data sets. In this context, it becomes necessary for econometricians to understand what these two cultures are, what opposes them and especially what brings them together, in order to appropriate tools developed by the statistical learning community to integrate them into econometric models.

1. Related work

Cyclic booms and busts have been a feature of economic life and one of the major arguments against capitalism since the eighteenth century. (Ayres, R. 2020). The cyclical nature of the Russian economy, its susceptibility to alternating booms and booms, is still poorly understood, although the recent crisis has generated a flurry of publications covering various aspects of the crisis in Russia. These publications, however, are largely journalistic in nature and do not yet allow to form a holistic idea of the nature of the crisis unfolding in the world economy, its driving forces and possible consequences, as well as the mechanism for overcoming the crisis and the degree of influence of these processes on the Russian economy.

The theoretical influence of economic cycles on time-varying risk premiums is then explained based on two key economic concepts: nominal GDP and adaptive expectations. (Raffinot, T. (2017) The economic cycle is thus a fundamental yet ambiguous concept, since it can refer to conceptually different global economy fluctuations.

On the functioning of the economy, many theories exist on the variables that need to be analyzed in order to keep a quick overview of economic trends. Ensemble machine learning algorithms, referred to as random forest (Breiman (2001)), are applied to quickly and accurately detect economic turning points in the United States and in the euro area. Genetic programming (GP) has been successfully used as a machine learning tool for automatic problem- solving in many areas such as image processing (Harding et al., 2013), but very seldom for macroeconomic modelling and forecasting (Alvarez-Diaz, 2019, Claveria et al., 2019, 2020). This article uses an extended set of indicators for the forecast: GDP in constant 2010 US $, population in absolute values are added to macroeconomic parameters, data are added not only on unemployment, but also on labor force, as well as manufacturing production. Exports and imports of goods are added to the indicators of the international economy, the analysis includes not only foreign direct investment, but also portfolio investment, current account balance. More financial indicators are used, related to the exchange rate, stock markets and cross-border transactions. This study does not consider factors that are stable over the analyzed period (such as the area of the country, forest areas), generalized indicators for the general situation in certain sectors of the economy, as well as evaluative indicators (such as the political and social atmosphere) unlike the study conducted by Chukiat et al, (2019) which uses qualitative information, quantitative trends and social movement activities. However, the Random Forest (RF) algorithm showed high accuracy in predicting GDP with an accuracy of 0.70 and a Kappa coefficient of 0.41 in the study by Chukiat et al.(2019) and in ours an accuracy of 0.78 and a Kappa coefficient of 0.49.

2. The methods of the research

The objective of this paper is to computationally predict economic structural trends in Russia by applying machine learning. The data used consists of mixed observations such as qualitative survey details and time trend data series from 1990 to 2020, that are used to perform econometric estimation by artificial intelligent approaches. All variables are described and presented in Table 1. Technically, the collective variables used in this paper were collected from reliable sources that have managed to store information from the world trends for convenient access, for example, FRED (Federal Reserve Economic Data), Federal Budget of the Russian Federation, World Bank Database, World Trade Organization, Bank of Russia, etc.

The modern economic theory is based on the idea that the cycle is primarily about output and employment fluctuations. The trend sets the level of potential output corresponding to the production capacity of the economy at full employment. The growth in potential output is a consequence of the growth of production opportunities and is described by the models of economic growth. Growth is associated with the accumulation of factors of production (capital accumulation, growth in the labor force, productivity growth). Growth rates depend on long-term trends; therefore, a significant change in potential output occurs only in the long run, while in the short run it is considered constant. Manufacturing capabilities affect aggregate supply.

The cyclical component describes short-term fluctuations in the observed GDP around a trend. The economy grows faster or slower than the trend, de- pending on how intensively the resources available in it are used. With excessively intensive use, it grows faster than the trend, with insufficient intensive use it grows slower.

In the following research we selected the following group of factors:

– National Currency

With an increase in the exchange rate, on the contrary, exports become unprofitable, which can lead to a reduction in export industries and national production in general, and the volume of imports increases. The import of foreign investments is growing. The real amount of external debt, expressed in depreciated foreign currency, is decreasing. The devaluation of the ruble taking place today is an ambiguous process. In the short term, of course, this affects the population and its income. But, on the other hand, this creates more favorable conditions for Russian manufacturers, because their products are becoming more competitive in the domestic and international markets. Traditionally, it is believed that the weakening of the ruble is beneficial to exporting companies. But the benefits from the weakening ruble for oil companies as exporters of raw materials does not outweigh their losses because of the growth of the corresponding tax burden tied to the national currency exchange rate.

– State finance

This group includes expenses, income, external debt, account balance and military expenses, etc. Russia is characterized by a high level of state participation in the economy. Large companies, with state participation dominate on the national market. Government funding and their effectiveness directly determine economic growth and diversification. With a significant amount of public external debt, most of the federal budget funds are spent on reducing the deficit in the consolidated budget, therefore, there is a decrease in expenditures for the development and expansion of production within the country, for social needs, as a result, everything affects the living standards of people. Thus, there is a slowdown in the country's economic growth.

– Stock Market

This group includes share market, stock market indices, number of registered companies, etc. The stock index is the main indicator of the stock market, which is based on the prices of a group of securities, reflects the state and dynamics of the securities market. Stock markets around the world are interconnected through communication channels, and information can spread to investors very quickly. The change in the index over time allows us to judge the general di- rection of price movement. Pessimism in the stock market causes a decline in quotations, and optimism or a low level of pessimism in the market contributes to high trading volumes in the stock market and higher incomes. Pessimism and optimism equally affect the stock market in accordance with the theory of investor sentiment and the theory of timing for an IPO (market timing theory).

– Central Bank policy

Includes interest rate, Central Bank assets, etc. The interest rate is one of the most effective instruments for national economy regulation. The rate reduction will stimulate the economy. Borrowing becomes cheaper, in the beginning for banks, then for corporations and then for consumers. The demand for goods and services is growing. However, the global economy develops in cycles. And at a certain stage of economic recovery, the market overheats. In order to avoid landslide falls, regulatory authorities are taking measures to smooth out cyclical fluctuations by slowing down of economic processes by raising the interest rate.

– Macroeconomic factors

This group includes GDP, Industrial production index, inflation, international trade, etc. Essentially, GDP reflects the health of an economy, which can directly affect investor sentiment. You should also use the values of real GDP, which considers the extent to which GDP growth is determined by real growth in production, and not by price increases. The Industrial Production Index is an indicator of business cycles that affect price fluctuations in the stock market. The growth of the industrial production index reflects the development of existing sectors of the economy, which may cause an increase in the number of IPOs, and, on the other hand, may indicate the development of knowledge-intensive industries, whose innovative companies enter the capital markets in search of investments for development. Thus, they contribute to the creation of a higher level of industrial production. As for structural growth, it has been insignificant in the past seven years due to the orientation of the economy towards the export of raw materials while the share of innovative sectors has decreased. Due to the rigidity of prices, the general equilibrium in the economy in a short period is ensured by changes in quantity. When demand rises, firms increase production and hire additional workers, and when demand falls, they reduce production and lay off workers. Therefore, the observed GDP is greater or less than the potential GDP, respectively. In response to high inflation, it becomes unprofitable to make savings, open deposits, so bank clients withdraw money from their accounts. Russia is a major participant in the system of international trade relations. The development of international trade in the XX century. turned it into a decisive factor in economic growth for most countries in the world.

– Population

Rapid aging of the population is forcing the world to rethink fiscal, social and migration policies. This question is especially relevant for Russia, where, due to the "demographic trap" of the 1990s, the birth rate is declining faster than in developed countries. In Russia, the echoes of the Second World War remain in the demographic pyramid. As well as the consequences of the demographic slump of the 90s. Labor force affects labor productivity and the scale of production. As long as the labor market can absorb labor, labor productivity will rise. This creates the so-called "demographic dividend" of economic growth, which contributes to an increase in savings, savings and investment.

– Investments

The stock market indicators' outstripping economic fluctuations is explained by the desire of investors to predict the direction of economic development in order to sell assets at their peak or buy them at the lowest price. That is why the cyclical development of the stock market is ahead of the development of the economic cycle.

Table 1

The different variables and their sources

Variables	Range of time series	Sources
Real Effective exchange rate	1990-2008	Federal Reserve Economic Data
Government Expenditures	1990-2008	Federal Budget of the Russian Federation
Government Revenues	1990-2008	Federal Budget of the Russian Federation
Public debt (% per GDP)	1990-2008	Trading Economics
Military expenditures	1990-2008	Trading Economics
External debts stocks total (DOD US $) Russian Federation	1990-2008	The World Bank
Use of IMF credit (DOD current US$) Russian Federation	1990-2008	The World Bank
Stock Market Capitalization to GDP for Russian Federation	1990-2008	Federal Reserve Economic Data
Long-Term Government Bond Yields: 10-year: Main for the Russian Federation	1990-2008	Federal Reserve Economic Data
3-Month or 90-day Rates and Yields: Inter-bank Rates for the Russian Federation	1990-2008	Federal Reserve Economic Data
Interest Rates. Government Securities. Treasury Bills for Russian Federation	1990-2008	Federal Reserve Economic Data
Central Bank Assets to GDP for Russian Federation	1990-2008	Federal Reserve Economic Data
Total Share Prices for All Shares for the Russian Federation	1990-2008	Federal Reserve Economic Data
National Currency to US Dollar Exchange Rate: Average of Daily Rates for the Russian Federation	1990-2008	Federal Reserve Economic Data
Stock Market Total Value Traded to GDP for Russian Federation	1990-2008	Federal Reserve Economic Data
Number of Listed Companies for RF, Number of Listed Companies per Million People, Annual, Not Seasonally Adjusted	1990-2008	Federal Reserve Economic Data
Total Share Prices for All Shares for the Russian Federation, Index 2015=100, Annual, Not Seasonally Adjusted	1990-2008	Federal Reserve Economic Data
External debt stocks, long-term (DOD, current US$)	1990-2008	Federal Reserve Economic Data
GDP (constant 2010 US$)	1990-2008	The World Bank
GDP Growth annual %.	1990-2008	The World Bank
Inflation, %, consumer prices (annual %)	1990-2008	The World Bank
Population	1990-2008	United Nations
Population (growth rate)	1990-2008	Federal State Statistics Service
Labour force, total	1990-2008	The World Bank
Unemployment	1990-2008	The World Bank
Industrial value added. Industry, value added (% of GDP)	1990-2008	The World Bank
Agricultural value added. Agriculture, forestry, and fishing, value added	1990-2008	The World Bank
Total Manufacturing Production for the Russian Federation	1990-2008	The World Bank
Total merchandise exports (Russia), annual	1990-2008	World Trade Organization
Total merchandise imports (Russia), annual	1990-2008	World Trade Organization
Commercial services exports (Russia),	1990-2008	World Trade Organization
Commercial services imports (Russia), (Million US dollar)	1990-2008	World Trade Organization
Foreign direct investment, net inflows	1990-2008	The World Bank
Portfolio Investment, net (BoP, current US$)	1990-2008	The World Bank
Current account balance (BoP, current US$)	1990-2008	The World Bank

Total reserves (includes gold, current US$)	1990-2008	The World Bank
Official exchange rate	1990-2008	The World Bank
External debt stocks	1990-2008	The World Bank
Net international investment position	1990-2008	The World Bank
Cross-border transactions of individuals,Transfers from Russia, million USD	1990-2008	Bank Of Russia
Cross-border transactions of individuals,Receipts into Russia, mln USD	1990-2008	Bank Of Russia
Transfers from Russia made through money transfer systems, mln USD	1990-2008	Bank Of Russia
Transfers to Russia made through money transfer systems, mln USD	1990-2008	Bank Of Russia
Volume of money transfers, RUB billion (for the period)	1990-2008	Bank Of Russia
Transaction volume, RUB billion	1990-2008	Bank Of Russia
Volume of payments by credit institutions, RUB billion	1990-2008	Bank Of Russia

3. Forecasting methods and tools

3.1. Optimization of hyper-parameters

Before discussing the forecasting models, it is important to detail how the hyper- parameters are selected. Let us take the example of the auto-regressive model AR

$$y_{th} = \rho(L)Y_t + e_t \quad (1)$$

where the order $\rho(L)$ is the only hyper-parameter. To fix $\rho(L)$, the standard approach is the selection criterion. The Bayesian Information Criterion (BIC) is used in this case:

$$log\left(\frac{SCR_{pj}}{T}\right) + p_i . log\left(\frac{T}{T}\right) \quad (2)$$

Where scr_{pj} is the sum of squares of the residuals and where pj denotes the choice of auto-regressive order. Since the first term is decreasing in pj , the second term allows the BIC to regularize the over-fitting by penalizing with the number of parameters to be estimated.

Another way of optimizing parameters that is especially popular in machine learning is cross-validation (CV). Like BIC, CV also selects the optimal order p, but regularizes using out-of-sample prediction performance, whereas BIC selection is based solely on in-sample performance. The popularity of CV is also due to its simplicity, since it can be practiced even when the information criterion is not available. There are several approaches to CV, but the most popular is based on random resampling (K -fold) in the training period. Assume that the number of folds (fold) is fixed at five (another second-order hyper-parameter). This is equivalent to dividing the sample period into five equally sized sub-samples. Then, four sub-samples are used in turn to estimate model j of the previously presented grid (forming the training set in ML language), and one sub-sample is used to evaluate the out-of-sample performance with, usually, the mean square error (MSE) as metric. The element j of the grid producing the minimum MSE will be the optimal order estimate. In this paper we used cross-validation.

3.2. The proposed forecasting models

In this section of the article different models of the learning machine are used. These models are: Random Drills (RF), K-Nearest neighbors (KNN), Support Vector Machine (SVM).

- **Random Forests (RF)**

A random forest is machine learning algorithm that is made up of multiple decision trees to predict a result, and this collection of trees is often called an ensemble. It's powerful tool that is used in many industries to help companies make better decisions, reduce risk and maximize success. It's a very popular machine learning algorithm that can be used for classification and regression. The first model using a non-linear approximation is the random forest model (de Breiman, 2001).

A random forest consists of many decision trees, and every tree is built using a four-step process.

Step 1. Create a 'Random' Dataset : Bootstrapping
Step 2. Select 'Random' Attributes
Step 3. Select best attribute to split Step 4. Split the attribute
Step 2-4 are repeated until a tree is fully constructed.

Technically, the Random Forest algorithm is often shown as follows:
For b = 1 to B
1. Create a bootstrap sample, with replacement, B training examples from x, y. Label these x_b, y_b
2. Train the tree, f_b on x_b, y_b
3. Average the predictions or take the majority vote to arrive a final prediction.

'b' represents a single tree
'B' represents the entire forest

Like decision tree, each tree in random forest is no different, except that is built from a 100 % unique training dataset.

This is accomplished by selecting random examples from the original training dataset and recreating the dataset for each tree. Technically, this is called bootstrapping, which is a statistical technique that makes use of sampling. A major benefit of random sampling is that every piece of training data is likely to be included, or represented, in at least one tree in the forest.

After a random forest has created a new dataset, it randomly selects at- tributes to split. To do this, algorithm does two things:

First, it restricts how many attributes it will use for any given branch. To do this, it uses the square root of the number of attributes as the maximum of attributes it will consider.

Second, it randomly selects the number of attributes.

Next, the algorithm selects the best attribute to split. To do this, it makes use of entropy and information gain to determine the 'purity' of each split. The split with the greatest level of purity is selected.

To make a prediction, there are two ways that a random forest predicts: majority vote or mean.

Predicting with a majority vote - One option for making a prediction is to simply take a majority vote, which means that the class that is predicted most often within the forest is selected as the algorithm's final prediction. This approach works very well for categorical classes, such as 'Yes' and 'No' or 'Dog' and 'Cat'

Predicting with the mean - Second option for predicting is to use the mean, or average, of the result of all the trees in the forest. This is calculated by using the following formula:

$$\hat{y} = \frac{1}{T}\sum_{b=1}^{B} y_b(x') \quad (3)$$

ŷ: is the final prediction for the random forest.
y_b: represents a single tree.
T: represents the total number of trees in the random forest.
x′: represents the prediction of each class for a single tree

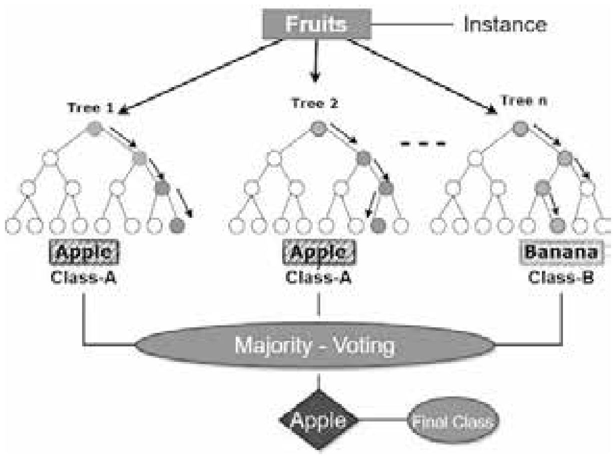

Fig. 1. Decision tree with depth of 4.

- **K-Nearest neighbors (KNN)**

The K-Nearest Neighbors (KNN) classifier is one of the most widely used classification algorithms in machine learning that belongs to the supervised learning category. This algorithm can be used in regression problems. It records all valid attributes and classifies new attributes based on their similarity dimension. KNN is a statistical recognition model method for detecting different classes in a model. A tree data structure is used to determine the distance between the point of interest and the points in the training data set.

The attribute is classified by its neighbors. In the classification method, the value of k is always a positive integer closest to the neighbor. The nearest neighbors are selected from a set of classes or property values of the object.

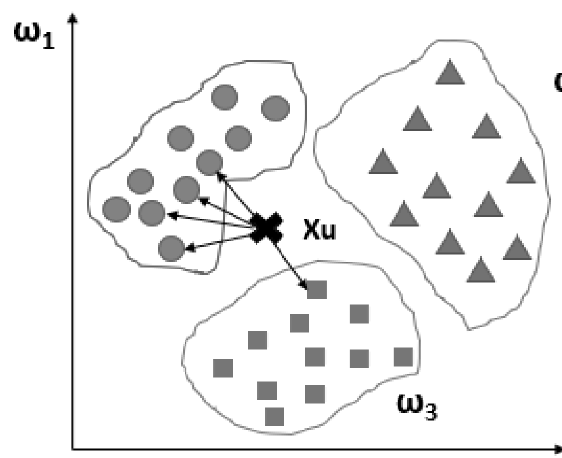

Fig. 2. Assignment of observations to clusters of classes w1, w2 and w3

- **Support Vector Machine (SVM)**

The support vector machine algorithm is used to solve classification problems and regression [3]. This algorithm is a relatively new approach and has shown good performance in recent years. The support vector machine algorithm is based on linear classifiers and in line-separated data, this algorithm isolates objects into specified classes [4]. It can also identify and classify instances that are not supported by the data. The only extension of this algorithm is to perform a regression analysis to obtain a linear function, and another extension teaches how to classify items to obtain a classification of individual items.

3.3. Model validation

As in econometrics, it is difficult to give better results in machine learning. For the validation of the model in this article we will use Cohen's Kappa coefficient (k). [5] Cohen's Kappa coefficient is a statistical tool that measures the agreement between two raters, determining to which category a finite number of items belong, and represents the degree of accuracy and reliability in a statistical classification. The value of Kappa can be negative, i.e., less than 0. A score of k=0 means that there is random agreement between the raters, while a score of k=1 means that there is complete agreement between the raters. Therefore, a score of k less than 0 means that there is less agreement than random. Cohen's co-efficient Kappa remains calculated by this formula:

$$k = \frac{p_0 - p_e}{1 - p_e} \quad (4)$$

Where p_0 is the observed relative agreement between raters, which identifies accuracy, and is the hypothetical probability of strong agreement. The observed data are used to calculate the probabilities of each randomly observable view in each category [5]. For categories k, a number of elements n and is the number of time evaluators n_{ki} is the number of time evaluators i predicted category k,

$$p_e = \frac{1}{N^2} \sum_k n_{k1} \cdot n_{k2} \quad (5)$$

4. Empirical results

4.1. Descriptive information

The figure below shows Russia's economic trends through its annual collective GDP from 1990 to 2008 between actual and forecast. The ranking of the reality trends clearly shows that the Russian economy fluctuates considerably. This fluctuation makes prediction more difficult, as traditional econometric tools cannot provide the best model, so Newton's method was used to extend the explanatory power of the data. The empirical results show that the peak period is defined at the level, which is above the optimal value (5%). The graph below shows the Russian GDP from 1990 to 2008 between actual and forecast values.

4.2. The results of the machine learning algorithm

This step is the comparison of different machine learning models. For this com- parison we used cross test validation. Three machine learning algorithms were used namely K-NN, Random Forest and SVM. The data set will be divided into two parts. 75% of the data is used to train the models, and 25% of the data is used to perform tests.

The results are presented in Table2. In this calculation Random Forest (rf) is the best model and contains the highest parametric values when selecting by accuracy values and Kappa coefficient, which are 0.78 and 0.49 respectively.

The Random Forest algorithm has the highest score among the machine learning algorithms used for the prediction of macroeconomic variables in Russia. Moreover, the mean absolute error (MAE) of this algorithm is 0.012595 and the root mean square error (RMSE) is 0.017032.

Predictions show the following peaks – 1998 and 2008. We can give a proper economic interpretation. The recovery of the economy after reforms began in 1996-1997. Price liberalization, capital movements and large-scale privatization of enterprises at undervalued prices led the economy to default in 1998- a deep economic recession, the depreciation of the ruble, and a drop in income. The devaluation and freed-up capacity gave the economy a boost, growing 6.4% in 1999 and 10% in 2000. From 1999 to 2008, the Russian economy showed GDP growth at an average of 7% per year. By 2008, Russia's GDP had almost doubled, the poverty rate had halved, foreign direct investment had risen from $14.3 billion in 2001 to $121.1 billion in 2007. As a result, Russia continued to attract the attention of investors.

Table 2

Summary table of results

Models	Hyper-parameters	Accuracy	Kappa's Coefficient
Random Forest (rf)	Max-depth = 3 N-estimators = 100 Criterion = gini Max-features = 0.0693	0.7810	0.4999
SVM (svm)	C = 246.4819 Gamma = scale Class-weight = balanced	0.7190	0.5
KNN (knn)	N-neighbors = 14, p = 3	0.5571	0.125

Conclusion

We use several economic variables in order to make a prediction. Machine learning systems can handle a huge number of informative details in databases, including qualitative data, quantitative factors and even time series trends. In this paper, 30 time series variables concerning the economic structures of Russia from 1990 to 2008 were included to predict the reasonable future trend. due to relative economic stability, to exclude external influence on the results. The obtained results show that the Random Forest is the best selected model. As a conclusion, we can say that machine learning is the appropriate solution for money-econometric research in Russia. In an unfavorable institutional environment, even low inflation can have a negative impact on economic growth, allowing more to save rather than spend. Let us also pay attention to the traditionally ignoring the business cycle nature of Russian monetary and budgetary policy, which in modern conditions is actually becoming pro-cyclical.

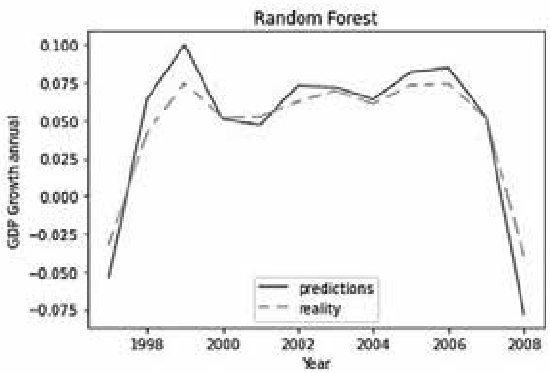

Fig. 3. Russian economic forecasts from 1998 to 2008.

The dependence of the Russian economy on external demand for raw materials and on world trends formed by world economic and political centers is one of the reasons for the absence in Russia of the need for autonomous forecasts of cyclical fluctuations. Implementing the ML techniques, we were able to increase the accuracy of our results. With advanced artificial calculations, the empirical result is very precise to real situations. We believe that the bunch of ML techniques will ensure and support further research in this field.

References

1. *Dalibor, S.* : Prévision macroéconomique dans l'ère des données massive et de l'apprentissage automatique.
2. *M. Khichane* : Le machine Learning par la pratique. Edition ENI
3. *Chaiboonsri, Chukiat Wannapan, Satawat.* (2019). Big Data and Machine Learning for Economic Cycle Prediction: Application of Thailand's Economy. https://doi.org/10.1007/978-3-030-14815-7_29.
4. *Pontius, R.G. and Millones, M.* (2011) Death to Kappa: Birth of Quantity Disagree- ment and Allocation Disagreement for Accuracy Assessment. International Journal of Remote sensing, 32, 4407-4429.
5. *Cortes, C. and V. Vapnik,* Support-vector networks. Machine learning, 1995. 20(3): p. 273-297.
6. *Raikwal, J. and K. Saxena,* Performance evaluation of SVM and k-nearest neighbor algorithm over medical data set. International Journal of Computer Applications, 2012. 50(14).
7. *Abdi, M.J. and D. Giveki,* Automatic detection of erythemato-squamous diseases using PSO–SVM based on association rules. Engineering Applications of Artificial Intelligence, 2013. 26(1): p. 603-608.
8. Ministry of finance of Russian federation: http://minfin.gouv.ru
9. *Wannapan, S., Chaiboonsri, C., Sriboonchitta, S* : Prévision macro-économétrique pendant les périodes du cycle économique à l'aide d'un algorithme bayésien d'optimisation des valeurs extrêmes. Dans : Kreinovich, V., Sriboonchitta, S., Chakpitak, N. (eds.) TES 2018. SCI, vol. 753, p. 706 à 723. Springer, Cham (2018).
10. *Chakraborty, C., Joseph, A.* : L'apprentissage automatique dans les banques centrales. Document de travail n° 647 des services de la Commission. Banque d'Angleterre (2017).
11. *Bholat, D.:* Big data and central banks. Q. Bull. Q1, pp. 86-93 (2015). https://www.researchgate.net/publication/276101527_Big_Data_and_central_banks
12. *Chakraborty, C., Joseph, A.*: Machine learning at central banks. Stuff Working Paper No 647. Bank of England (2017).
13. *Hinge, D.*: Big Data in Central Banks. Published by Infopro Digital services Ltd. Central Banking Publications, London (2017).
14. *Signorini, L.F.* Harnessing big data machine learning technologies for central banks. The Printing and Publishing Division, Bank of Italy, Rome (2018).
15. *Coulombe, Philippe Leroux, Maxime Stevanovic, Dalibor Surprenant, Stéphane.* (2020). How is Machine Learning Useful for Macroeconomic Forecasting?
16. *Lahiri, S.N.* (2003). Resampling Methods for Dependent Data. Springer.
17. *Raffinot, Thomas.* (2017). Asset Allocation, Economic Cycles and Machine Learning.

18. *Hull, Isaiah.* (2021). Machine Learning and Economics. https://doi.org/10.1007/978-1-4842-6373-0_2.
19. *Statistics, L.B. Breiman, L.* (2001). Random forests. Machine Learning. 5-32.
20. *Ayres, Robert.* (2020). Economic Cycles, in Principle. https://doi.org/10.1007/978-3-030-39651-0_16.

Amos B.K. PhD student in IT, Department of Information Technologies, Peoples' Friendship University of Russia (RUDN), 6 Mikluho-Maklaya St, Moscow, 117198, Russian Federation, e-mail: broukouameamos9@gmail.com

Smirnov I.V. Associate Professor, Department of Information Technologies, Peoples' Friendship University of Russia (RUDN), 6 Mikluho-Maklaya St, Moscow, 117198, Russian Federation and also Head of Department No. 72, FIC "Informatics and Control" RAS, Institute for Artificial Intelligence Problems, Moscow, e-mail: ivs@isa.ru

Aidrous I.A. PhD. in Economics, Associate Professor at the Institute of World Economy and Business, Peoples' Friendship University of Russia (RUDN), 6 Mikluho-Maklaya St, Moscow, 117198, Russian Federation, e-mail: aidrous@mail.ru

Asmyatullin R.R. PhD. in Economics, Associate Professor at the Institute of World Economy and Business, Peoples' Friendship University of Russia (RUDN), 6 Mikluho-Maklaya St, Moscow, 117198, Russian Federation, e-mail: rav.asmyatullin@gmail.com

Glavina S.G. PhD. in Economics, Head of the Digital Economy Programme at the Institute of World Economy and Business, Peoples' Friendship University of Russia (RUDN), 6 Mikluho-Maklaya St, Moscow, 117198, Russian Federation, e-mail: sofiya.glavina@gmail.com