# Forecasting Recessions in the US Economy Using Machine Learning Methods

Nikolay Zyatkov
*Institute of Computational Mathematics and Mathematical Geophysics SB RAS*
Novosibirsk, Russia
nikolay.zyatkov@gmail.com

Olga Krivorotko
*Institute of Computational Mathematics and Mathematical Geophysics SB RAS*
Novosibirsk, Russia
krivorotko.olya@mail.ru

***Abstract*—A quantitative analysis of socio-economic characteristics, the set of which is typical in the pre-crisis periods of a market economy, is carried out. An indicator for forecasting the onset of a recession in the US economy over the next 6, 12 and 24 months has been constructed using machine learning methods (k-nearest neighbors, support vector machine, fully connected neural network, LSTM neural network, etc.). Using roll forward cross-validation, it is shown that the smallest error in predicting the onset of future recessions was obtained by a fully connected neural network. It is also shown that all three constructed indicators successfully predict the onset of each of the last six recessions that occurred in the United States from 1976 to 2021 (Early 1980s recession, Recession of 1981–82, Early 1990s recession, .COM bubble recession, Great Recession, COVID-19 recession). The resulting indicators can be used to assess future economic activity in the United States using current macroeconomic indicators.**

***Index Terms*—recession, financial crisis, US economy, machine learning, deep learning, socio-economic processes**

## I. Introduction

The modern market economy is a complex dynamic system subject to cyclicality. Such business cycles (or economic cycles or boom-bust cycles) refers to economy-wide fluctuations in production, trade, and general economic activity. From a conceptual perspective, the business cycle is the upward and downward movements of levels of GDP (gross domestic product) and refers to the period of expansions and contractions in the level of economic activities (business fluctuations) around a long-term growth trend. Business cycles can be divided into several phases: expansion, peak, contraction, and trough. In this paper, we will quantitatively investigate the contraction phase of business cycles for the US economy.

The classic definition of a recession is a decline in the real GDP of an economy for two quarters in a row [1]. At the same time, there is a private non-profit organization called the National Bureau of Economic Research (NBER), which has been the main source of information on business cycles in the United States (since 1854). The NBER adheres to its own methodology for diagnosing a recession, defining it as a significant decline in economic activity over a period of more than a few months, covering industrial output, employment, real income, wholesale and retail trade.

This work is supported by the Russian Science Foundation (project no. 18-71-10044).

The causes of recessions and business cycles remain an open question, as there is no global consensus on how the economy functions. There are a number of studies in which the authors build predictive models for the onset of recessions using mathematical and statistical methods [2]–[4]. Papers [5]–[8] show the application of machine learning methods for predicting recessions. For example, paper [5] describes the use of a machine learning approach known as boosted regression trees (BRT). The authors used 35 leading indicators related to the German economy, which were collected monthly. In [6], the authors apply random forest machine learning approach to predict US and UK GDP from 1990 one, three and six quarters ahead. [7] takes a similar approach to predict Italian GDP from 1995 to 2019 using several autoregression models and machine learning methods such as support vector machine, k-nearest neighbors and boosted trees. Paper [8] proposes a methodology for forecasting economic recessions using Machine Learning algorithms. Among the methods examined are Artificial Neural Networks (ANN), Support Vector Machines (SVM) and Random Forests. The datasets analysed refer to six countries (Australia, Germany, Japan, Mexico, UK, USA) and cover a time span of more than 40 years.

This paper proposes forecasting recessions in the US economy using machine learning methods for 9 leading macroeconomic indicators (see Section II). The use of machine learning is justified by the fact that more than 60-year history of macroeconomic data of the US economy has been accumulated. We are based on the assumption that there are reasons for the occurrence of recessions and there are combinations and values of economic indicators that anticipate recessions in advance. The paper compares the effectiveness of the most popular machine learning methods: logistic regression, k-nearest neighbors, support vector machine (SVM), random forest, fully connected neural network, neural network based on LSTM layer, which are described in Section III, and the comparison result in Section V. Deep optimization of the indicated methods is applied on US macroeconomic data by dividing them into training, validation and test samples, as well as the use of the roll forward cross-validation technique (see Section IV).

978-1-6654-0562-1/21/$31.00  

## II. Model construction and data selection

The NBER website provides data on the start and end dates of all recessions that have occurred in the United States since 1854. Table I lists such recessions in the US economy from August 1957 to the present day.

TABLE I
Recessions start at the peak of a business cycle and end at the trough.

| Recession start | Recession end | Description |
|---|---|---|
| 1957-08 | 1958-04 | Monetary policy tightening during the two years preceding 1957, followed by an easing of policy at the end of 1957 |
| 1960-04 | 1961-02 | Monetary recession occurred after the Federal Reserve began raising interest rates in 1959 |
| 1969-12 | 1970-11 | Fiscal and monetary tightening due to Vietnam War |
| 1973-11 | 1975-03 | The 1973 oil crisis |
| 1980-01 | 1980-07 | Tightening of the Fed's monetary policy to fight the inflation of the 1970s |
| 1981-07 | 1982-11 | Tight monetary policy to control inflation |
| 1990-07 | 1991-03 | 1990 oil price shock |
| 2001-03 | 2001-11 | Collapse of the dot-com bubble |
| 2007-12 | 2009-07 | Great Recession (collapse of the US housing bubble) |
| 2020-02 | 2020-04 | COVID-19 Recession |

We are building a model that predicts the likelihood of a recession starting over the next $X$ months. For $X$ we take 3 values: 6 months, 12 months and 24 months. When choosing data (features) to predict the occurrence of future recessions, we proceeded from the assumption that prediction of a recession, as already noted in the introduction, is a prediction of fluctuations in the US GDP curve. The future value of US GDP depends on the behavior and expectations of the following macro-agents: producers (businesses), consumers (households), and the government. Households offer their time in the labor market and consume the goods and services produced by the business. A business for the production of goods and services receives loans and borrowings in the debt market, the cost of which depends on the interest rate set by the Fed. Also macroagents can deal with investments. To describe these properties, we tried to take leading macroeconomic indicators in order to fix the expectations of businesses, households, governments and investors regarding their future economic activity, since these expectations affect future GDP. For example, we do not use the indicator of US GDP data, since the data for this macro indicator are published quarterly with a lag of 3 months and do not reflect the current or future state of affairs in the economy. To build a forecast of future recessions, we used monthly data of US macroeconomic indicators from August 1955 to October 2020. Used 9 socio-economic characteristics of the United States (Fig. 1):

- **Effective Federal Funds Rate**. The main instrument by which the Fed (the central banking system of the United States) can conduct its monetary policy.
- **Consumer price index (CPI)**. This is an indicator of the dynamics of US inflation, which decreases during recessions due to falling demand for goods and services.
- **Gold price per ounce**. This is an indicator of the dynamics of the world commodity market. In the event of inflation expectations, market participants seek to protect their savings by buying real goods. It can also reflect the dynamics of the dollar exchange rate, since the price of gold is denominated in dollars. It is also a traditional protective instrument in the event of world collapses, increased geopolitical risks and wars.
- **10 Year treasury rate**. This is a loan instrument for the US Government for a long term (10 years). If a recession is expected, market participants seek to reduce the share of risky assets in their portfolio and increase the share of defensive assets (for example, 10-year US treasury notes), which leads to a decrease in long-term interest rates.
- **Yield curve**. This is the difference (spread) between US long-term (10-year) interest rates and short-term (3-month) interest rates. If a recession is expected, the spread becomes negative due to increased investor demand for long-term protective instruments.
- **S&P 500 Index**. This is the price index for the top-500 US stocks. Before the onset of a recession in the 7-10 year business cycle, the S&P 500 tends to be near its all-time highs/local highs. At the start of the recession, the US stock price declines due to falling investor demand for risky assets.
- **Nonfarm payrolls**. This indicator describes the state of the US labor market. In our opinion, it is a more preferable macroeconomic indicator for predicting recessions than the unemployment rate due to the propensity of employers not to create new jobs in case of expectation of a recession.
- **Purchasing Managers' Index (ISM PMI)**. This indicator describes the expectations of business (manufacturers) regarding the US economy. It is a composite index published monthly by the Institute for Supply Management (ISM) based on a survey of 300 US industrial companies about their performance last month in 5 areas: new orders, production, employment, supplier deliveries, inventories.
- **University of Michigan Consumer Sentiment Index**. This indicator describes the expectations of households (consumers) regarding the US economy. Published by the University of Michigan Research Center. Every month, at least 500 telephone interviews are conducted with the US population to assess their confidence in the current economic situation. When this indicator decreases, households tend to spend less.

## III. Supervised Machine Learning Methods

Supervised machine learning methods are a class of mathematical methods that are characterized not by a direct problem solution, but by training and identifying empirical patterns on a set of $n$ experiments (historical data) $X = \{x_i\}$, with previously known results $Y = \{y_i\}, i = 1, \ldots, n$. Each object $x_i$ from $X$ is characterized by $p$ features, i.e. $x_i = \{x_{i1}, ..., x_{ip}\}$. In this paper $x_i$ represents the values of

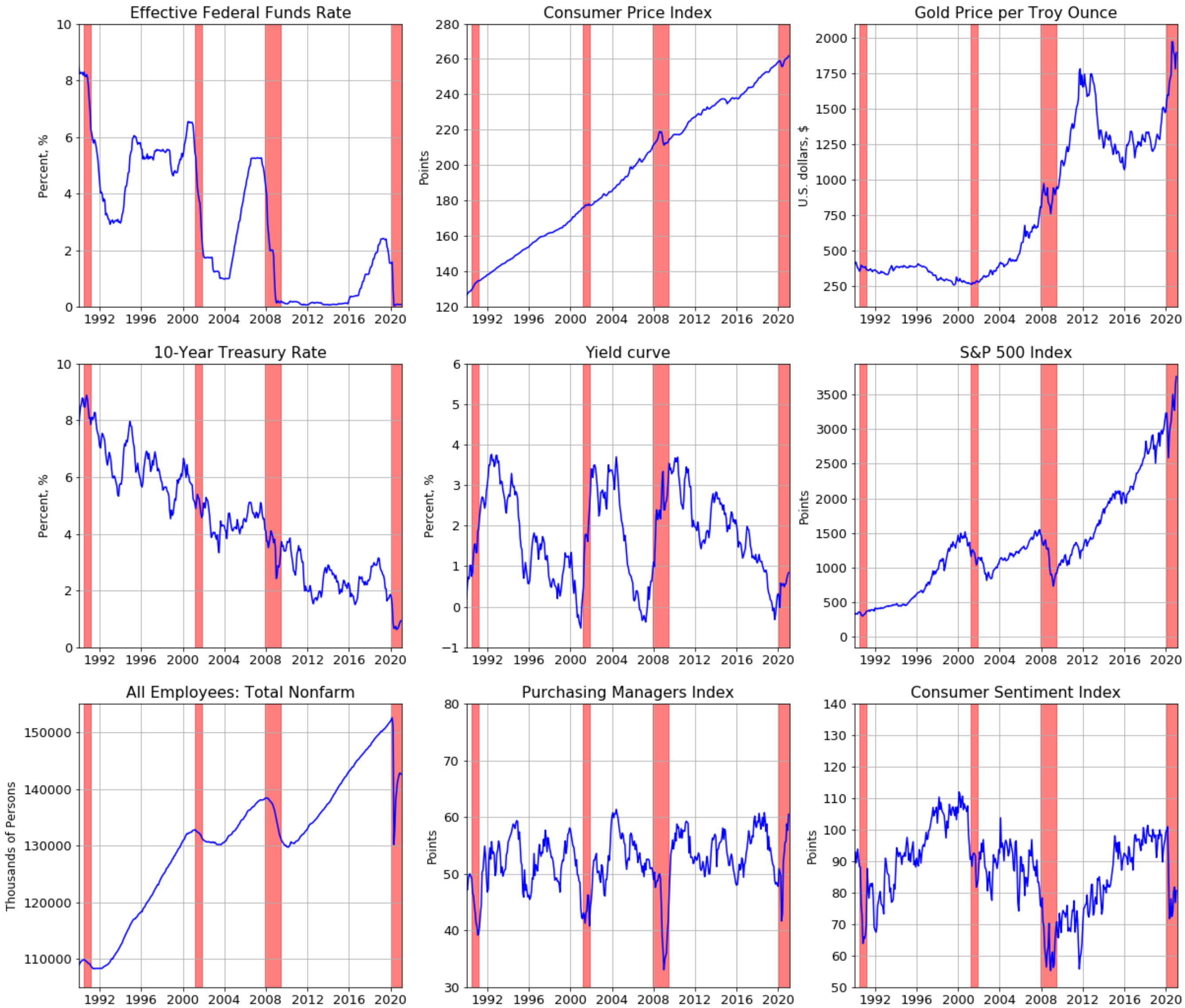



Fig. 1. Macroeconomic indicators of the US for the period 1990 to 2020, selected to forecast future recessions and recessions for this period (red areas).

the indicators shown in Fig. 1 for a certain date with the number $i$. From a mathematical point of view, the goal of machine learning is to restore the implicit function $f(x, y)$ from a finite set of pairs $\{(x_i, y_i)\}, i = 1, \ldots, n$ (training) and then using this function on new data (prediction) that has not been trained.

To predict the likelihood of recessions occurring within 6, 12 and 24 months, this paper considers classification problems using seven supervised machine learning methods described in the section below.

### A. Regularized Logistic Regression

Logistic regression is one of the basic machine learning algorithms. The algorithm requires to restore a linear function of the form:

$$g(x) = w_0 + w_1 x_1 + w_2 x_2 + \ldots + w_p x_p = w_0 + \mathbf{w}^T x, \quad (1)$$

namely, the coefficients $w_0, w_1, \ldots, w_p$ from the known data sets (features) $X = \{x_i\}, i = 1, \ldots, n$ and the corresponding target values $y_i \in [0; 1]$. This hyperplane should optimally divide the data $X$ into two classes, usually encoded with numbers 0 and 1. The process of deciding which class the new object $x^*$ belongs to is as follows:

- if $g(x^*) > 0$, then $y^*$ belongs to the class "1";
- if $g(x^*) < 0$, then $y^*$ belongs to the class "0";
- if $g(x^*) = 0$, then $y^*$belongs to the hyperplane (1) and it is impossible to unambiguously determine which class the object $x^*$ belongs to.

To pass from classification to the probability of a point $x^*$ belonging to the class "1", a sigmoid function is introduced:

$$\sigma(t) = \frac{1}{1+e^{-t}}.$$

The range of values of this function belongs to the interval $(0, 1)$, $\sigma(t) < 0.5$ for $t < 0$ and $\sigma(t) \geqslant 0.5$ for $t > 0$. To restore the optimal hyperplane (1) the following cost function is minimized:

$$Q(\mathbf{w}, x) = -\frac{1}{n}\sum_{i=1}^{n}(y_i \ln \hat{p}_i + (1-y_i)\ln(1-\hat{p}_i)), \qquad (2)$$

where $\hat{p}_i = \sigma(g(x_i))$ is the probability of belonging $x_i$ to class "1", $y_i$ – true value (equal to 0 or 1).

To eliminate the problem of overfitting (when the prediction error is large compared to the modeling error on the training data), it is necessary to apply regularization. For this, a penalty function (3) with the regularization parameter $\alpha \in (0, 1)$ is added to the cost function (4):

$$R(\mathbf{w}) = r\sum_{i=1}^{n}|w_i| + \frac{1-r}{2}\sum_{i=1}^{n} w_i^2. \qquad (3)$$

$$Q(\mathbf{w}, x, \alpha) = -\frac{1}{n}\sum_{i=1}^{n}(y_i \ln \hat{p}_i + (1-y_i)\ln(1-\hat{p}_i)) + \alpha R(\mathbf{w}). \qquad (4)$$

A regularization of the form (3) is a combination of $L_1$ and $L_2$ regularizations. The first term in the expression (3) takes into account the most important features, and the second term smooths the result. The $r$ and $\alpha$ parameters are specified in Table II and restored using the optimization method.

TABLE II
LOGISTIC REGRESSION PARAMETERS

| Parameter | Characteristic | Range |
|---|---|---|
| $\alpha$ | Regulation parameter from (4) | $(0; 1)$ |
| $r$ | Usage rate of $L_1$ and $L_2$ regularization from (4) | $[0; 1]$ |

### B. K-nearest Neighbors

This algorithm in a trivial way for a new object $x^*$ finds the $k$ nearest objects from the training set $X$. In the case of classification, the algorithm makes a decision based on the number of objects (from $k$ nearest neighbors) belonging to each class. The more objects belong to a given class, the more likely it is that the new object belongs to that class. The $k$ parameter is specified in Table III and restored using the optimization method.

TABLE III
K-NEAREST NEIGHBORS PARAMETERS

| Parameter | Characteristic | Range |
|---|---|---|
| $k$ | Number of nearest neighboring objects | $[1; 100]$ |

### C. Support Vector Machine (SVM)

To classify objects into 2 classes, as in the case of the logistic regression method (see Subsection III-A), it is necessary to find a separating hyperplane in the form of (1) that at the same time maximizes the distance from this hyperplane to "Class 1" and the distance from this hyperplane to "Class 2". For a detailed description of this method, see the book [9]. The main parameters of Support vector machine method are specified in Table IV and restored using the optimization method.

TABLE IV
SUPPORT VECTOR MACHINE PARAMETERS

| Parameter | Characteristic | Range |
|---|---|---|
| $C$ | $L_2$ regularization parameter | $[0.0001; 10]$ |
| $\gamma$ | Parameter of the Gaussian radial basis function | $[0.01; 1]$ |

### D. Random Forest

The Random forest algorithm was proposed in [10] and is based on the execution of an ensemble of decision trees. The classification of objects is carried out by voting: each constructed tree assigns the object to be classified to one of the classes, and the class for which the largest number of trees voted wins. See the detailed description of the decision tree and random forest algorithms in [9].

The main parameters of Random forest method are specified in Table V and restored using the optimization method.

TABLE V
RANDOM FOREST PARAMETERS

| Parameter | Characteristic | Range |
|---|---|---|
| $n_{est}$ | The number of trees in the forest | $[1; 2000]$ |
| max depth | The maximum depth of the tree | $[5; 100]$ |
| min samples split | The minimum number of samples required to split an internal node | $[2; 10]$ |
| min samples leaf | The minimum number of samples required to be at a leaf node | $[1; 5]$ |
| max features | The number of features to consider when looking for the best split | |

### E. Gradient Boosting

Gradient boosting is another improvement to the decision tree algorithm. The gradient boosting algorithm is as follows:

- Step 1. The model is trained using the decision tree algorithm.
- Step 2. The forecast of the trained model is carried out on the same data.
- Step 3. The forecast error is calculated (the difference between the target values and the predicted ones)
- Step 4. The model is trained to predict the forecast error obtained in step 3.
- Step 5. Etc.: steps 3 and 4 are repeated iteratively until the stop criterion is met.

The final prediction is made as the sum of the predictions obtained in step 2 and steps 3 and 4.

The main parameters of Gradient boosting method are specified in Table VI and restored using the optimization method.

TABLE VI
GRADIENT BOOSTING PARAMETERS

| **Parameter** | **Characteristic** | **Range** |
|---|---|---|
| lr | Learning rate | $[10^{-5}; 0.1]$ |
| $n_{est}$ | The number of trees in the forest | $[1; 2000]$ |
| max depth | The maximum depth of the tree | $[5; 100]$ |
| min samples split | The minimum number of samples required to split an internal node | $[2; 10]$ |
| min samples leaf | The minimum number of samples required to be at a leaf node | $[1; 5]$ |
| max features | The number of features to consider when looking for the best split | |

### F. Fully Connected Neural Network

An artificial neural network allows modeling a non-linear function with some input and output data. Fully connected neural network has:

- input layer that contains of input parameters associated with the state of each neuron of the input layer.
- output layer in which the output parameters associated with the state of each neuron of the output layer are calculated.

If a neural network has additional layers between the input and output layers, then they are called hidden layers, and the training of such a network are called deep learning. Additional hidden layers can help the neural network identify more complex patterns between input and desired output data.

Each layer is connected to neighboring layers using weights and bias coefficients. The passage of information from the previous layer to the next is carried out according to the following rule: $z = Act(Wy+b)$, where $y$ is the vector of data on the previous layer, $z$ - vector of data on the next layer, $W$ is the weight matrix of the transition from the previous layer to the next, $b$ is the vector of bias coefficients. $Act$ is some activation function needed to eliminate linearity. There are a lot of activation functions. For example, it could be sigmoid function $Act(x) = \sigma(x)$.

Supervise learning of neural network means that for a given set of previously known input and output data (training data), it is necessary to select the optimal $W$ and $b$ coefficients so that the squared error between the exact output value and the output value obtained by propagating the input values through the neural network tended to minimum. The search for the optimal coefficients $W$ and $b$ is performed by the gradient descent method using the backward propagation of errors method [11].

### G. Neural Network Based on LSTM

The Long Short-Term Memory (LSTM) neural network was proposed in [12]. Unlike standard feedforward neural network LSTM can not only process single data points (such as images), but also entire sequences of data (such as time series, sound samples, text). Thanks to the LSTM's short-term and long-term memory mechanism, LSTM allows to identify patterns in these sequences. For a detailed description of this method, see the book [9].

## IV. Model Training Process and Roll Forward Cross-validation

The target vector $y$, by which the machine learning models were trained, was filled with values 1 and 0, describing two variants of events. The number 1 coded the class ”A recession in the US economy will come (or the economy is already in a recession) in a window from today's date to today's date plus 6/12/24 months.” The number 0 encoded all other cases. The values of the $y$ vector were filled based on the NBER data specified in Table I.

The process of training the model to predict data from y (using data $X$ – see Fig. 1) was carried out as follows: data from 1955 to 2020 were divided into a set of time windows, which in turn were divided into training, validation and test samples (Fig. 2). On the training sample (gray blocks in Fig. 2), machine learning methods were used to train predicting the onset of a recession in the United States for the next 6, 12 and 24 months according to the socio-economic characteristics indicated in Fig. 1.

The parameters of the models from Tables II, III, IV, V and VI were selected from the specified intervals in such a way as to minimize the error between predicted and true values on the validation samples (orange blocks in Fig. 2). And only then the model with optimal parameters was applied to the test sample (green blocks in Fig. 2). The search for the optimal parameters of machine learning methods (Tables II, III, IV, V, VI) were carried out using ”Optuna” hyperparameter optimization software. This package is based on the Tree-structured Parzen estimators. The algorithm also uses evolutionary methods (genetic algorithm, differential evolution), gradient (quasi-Newton, stochastic) and random search methods [13]. The results obtained from 1976 to 2020 (six test samples in Fig. 2: green blocks outlined with a red oval) were combined in the form of a time series, the range of values of which belongs from 0 to 1. Each value of such a time series describes the likelihood of belonging to the class ”A recession in the US economy will occur (or the economy is already in a recession) in a window from today's date to today's date plus 6/12/24 months.”

## V. Test Results

Table VII shows the result of minimizing the error in predicting the onset of future recessions with true data from 1976 to 2020. The rows of the table are sorted in ascending order of errors, obtained as a result of using machine learning methods. It can be seen that the smallest error in predicting the onset of future recessions was obtained using a fully connected neural network consisting of 9 input layer neurons, 8 hidden layer neurons with ReLU activation function [9] and

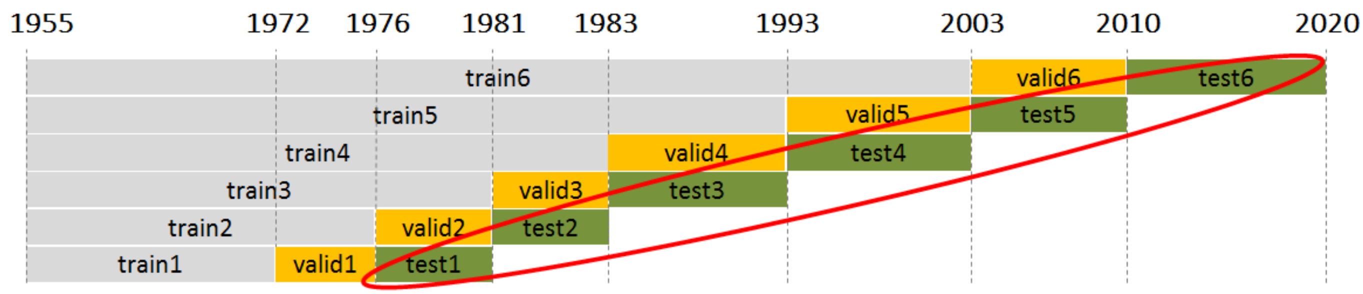



Fig. 2. Roll forward cross-validation.

2 output layer neurons with softmax activation function [9], in comparison with other methods.

TABLE VII
FORECASTING ERRORS FOR 6, 12 AND 24 MONTHS OF THE ONSET OF FUTURE RECESSIONS IN THE US ECONOMY USING MACHINE LEARNING METHODS.

| Machine Learning methods | 6 months | 12 months | 24 months |
|---|---|---|---|
| Fully connected neural network | 0.301 | 0.273 | 0.341 |
| Support vector machine | 0.315 | 0.313 | 0.374 |
| LSTM neural network | 0.319 | 0.336 | 0.426 |
| Gradient boosting | 0.459 | 0.437 | 0.468 |
| Random forest | 0.467 | 0.37 | 0.457 |
| Logistic regression | 0.531 | 0.463 | 0.469 |
| K-nearest neighbors | 0.537 | 0.57 | 0.629 |

Fig. 3 shows a comparison of the true values of the onset of recessions (red curve) and the forecast using a fully connected neural network (black curve) for periods of 6, 12 and 24 months. The function of true values can take two values: 0 and 1. Value 1 encodes the class ”The recession of the US economy will come (or the economy is already in a recession) in a window from the current date to the current date plus 6/12/24 months”. A value of 0 encodes the class ”The US economy recession will not occur in the window from today’s date to today’s date plus 6/12/24 months”.

The forecast function has a range of values $(0, 1)$ and describes the probability of belonging to the class ”The recession of the US economy will come (or the economy is already in a recession) in the window from the current date to the current date plus 6/12/24 months”. To estimate the forecast errors indicated in Table VII the logistic error function “logloss” $-y_t \ln(y_p) - (1 - y_t) \ln(1 - y_p)$ was used, where $y_t(t)$ is a function of true values, $y_p(t)$ is a function of predicted values. Fig. 4 shows the obtained indicators that predict the onset of last 6 recessions in the US economy for the roll forward cross-validation period from 1976 to 2021 (see Section IV). The red curve describes the forecast for the recession 6 months before its start, green – 12 months, blue – 24 months. The red areas on the graphs represent the periods of real recessions, according to the NBER data shown in Table I. In Table VIII, the last 3 columns show the dates on which each of the three indicators rises above 0.5, thus informing us of an impending recession in the US economy. The number of months/years before the official dates of the start of the recession, when these indicators became above 0.5, is indicated in parentheses. It can be seen, for example, that the short-term 6-month indicator for the first time gave a signal of the onset of a recession over the next 6 months (with a probability greater than 0.5) caused by the COVID-19 pandemic in March 2019 (11 months before its start), the medium-term 12-month indicator for the first time signaled the onset of this recession over the next 12 months (with a probability greater than 0.5) in August 2018 (1.5 years before its start), and the long-term 24-month indicator for the first time signaled the onset of this recession over the next 24 months (with a probability greater than 0.5) in September 2016 (3.4 years before its start).

## VI. FEATURES IMPORTANCE

Using the random forest method [10], we estimated the importance of each macroeconomic indicator in predicting the onset of a recession in the short-term (6 months), medium-term (1 year) and long-term (2 years) (see Table IX). The analysis shows that in the short-term period, PMI, CSI and S&P 500 are more important in forecasting recessions. In the medium and long term, the indicators of the yield curve, CSI, PMI and yield curve, CPI, Fed rate, respectively, are more important for predicting a recession.

## VII. CONCLUSION

A quantitative analysis of the US macroeconomic indicators, the set of which is typical in the pre-crisis periods of a market economy, is carried out. The indicators for predicting the onset of a recession in the US economy over the next 6, 12 and 24 months were constructed using a fully connected neural network. It is shown that all three constructed indicators successfully predict the onset of each of the last six recessions that occurred in the US from 1976 to 2021 using the roll forward cross-validation approach. The constructed indicators allow one to monitor the state of the US economy and enable investors to reduce in advance the share of risky assets in their portfolio as well as to develop a plan for managing a possible recession.

TABLE VIII

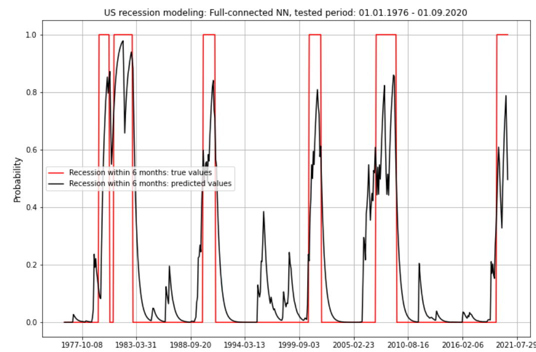
The results of the work of the obtained indicators for the six last US recessions from 1976 to 2021: the dates when the indicators first indicate the probability of the onset of a recession greater than 0.5. The number of months / years before the official dates of the start of the recession, when these indicators first became above 0.5, is indicated in parentheses.

| **Recession name** | **Start date of the recession** | **The date of the prediction of the recession by the indicator** | | |
|---|---|---|---|---|
| | | **”6 months” (red curve)** | **”12 months” (green curve)** | **”24 months” (blue curve)** |
| COVID-19 recession | 02.2020 | 03.2019 (11 m) | 08.2018 (1.5 y) | 09.2016 (3.4 y) |
| Great Recession | 12.2007 | 12.2007 (0 m) | 07.2006 (1.4 y) | 06.2005 (2.5 y) |
| .COM bubble recession | 03.2001 | 09.2000 (6 m) | 05.2000 (10 m) | 08.1999 (1.6 y) |
| Early 1990s recession | 07.1990 | 02.1989 (1.4 y) | 12.1988 (1.7 y) | 08.1988 (1.9 y) |
| Recession of 1981–82 | 07.1981 | 07.1981 (0 m) | 03.1981 (4 m) | 06.1979 (2.1 y) |
| Early 1980s recession | 01.1980 | 01.1980 (0 m) | 11.1979 (2 m) | 06.1979 (1.6 y) |

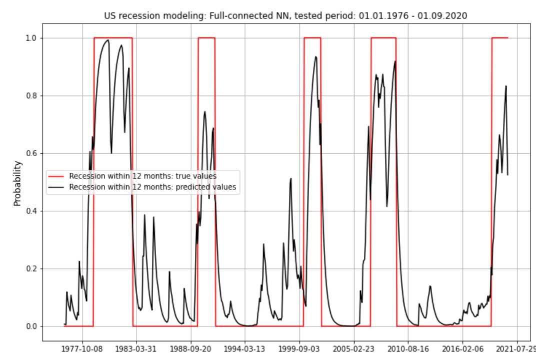
TABLE IX

Importance of each macroeconomic indicator in predicting the onset of a recession in the short-term (6 months), medium-term (1 year) and long-term (2 years) period.

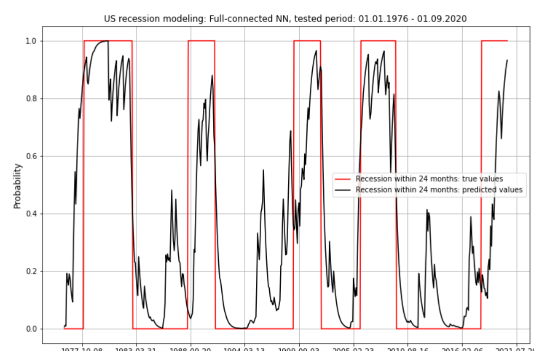
| **Macroeconomic indicator** | **6 months** | **12 months** | **24 months** |
|---|---|---|---|
| PMI | 0.165 | 0.124 | 0.075 |
| CSI | 0.164 | 0.165 | 0.110 |
| S&P 500 Index | 0.130 | 0.065 | 0.055 |
| Yield Curve | 0.115 | 0.185 | 0.230 |
| Nonfarm payrolls | 0.105 | 0.110 | 0.085 |
| PMI, 12m change | 0.075 | 0.080 | 0.050 |
| Fed Rate | 0.073 | 0.095 | 0.120 |
| CPI | 0.073 | 0.080 | 0.125 |
| 10-Year Rate | 0.060 | 0.070 | 0.098 |
| Gold Price | 0.035 | 0.040 | 0.075 |




a) 6 months




b) 12 months




c) 24 months

Fig. 3. The true values of the forecast of the onset of recessions for 6, 12 and 24 months (red curve) and predicted using a fully connected neural network (black curve).

## References

[1] S. Claessens and A. M. Kose, “What is a recession?” Finance & Development, vol. 46(1), pp. 52–53, 2009.

[2] A. Estrella and F. S. Mishkin, “Predicting U.S. recessions: financial variables as leading indicators,” The Review of Economics and Statistics, vol. 80(1), pp. 45–61, 1998.

[3] M. Chauvet and S. Potter, “Forecasting recessions using the yield curve,” Journal of Forecasting, vol. 24(2), pp. 77–103, 2005.

[4] J. Dovern and F. Huber, “Global prediction of re-cessions,” Economics Letters, vol. 133, pp. 81–84, 2015.

[5] J. Dópke, U. Fritsche and C. Pierdzioch, “Predicting recessions with boosted regression trees,” International Journal of Forecasting, vol. 33(4), pp. 745–759, 2017.

[6] R. Nyman and P. Ormerod, “Predicting economic recessions using machine learning algorithms,” arXiv 1701.01428, 2017, unpublished.

[7] G. Cicceri, G. Inserra and M. Limosani, “A machine learning approach to forecast economic recessions – an Italian case study,” Mathematics, vol. 8(2), pp. 241, 2020.

[8] A. Psimopoulos, “Forecasting economic recessions using machine learning: an empirical study in six countries,” South-Eastern Europe Journal of Economics, vol. 18(1), pp. 40–99, 2020.

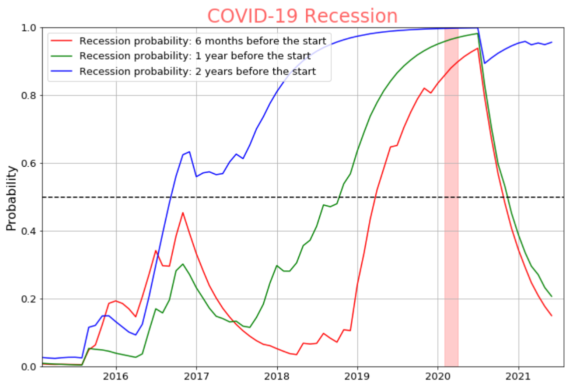
[9] A. Géron, Hands-On Machine Learning with Scikit-Learn and TensorFlow. Sebastopol, CA: O’Reilly Media, Inc., 2017.

[10] L. Breiman, “Random Forests,” Machine Learning, vol. 45, pp. 5–32, 2001.

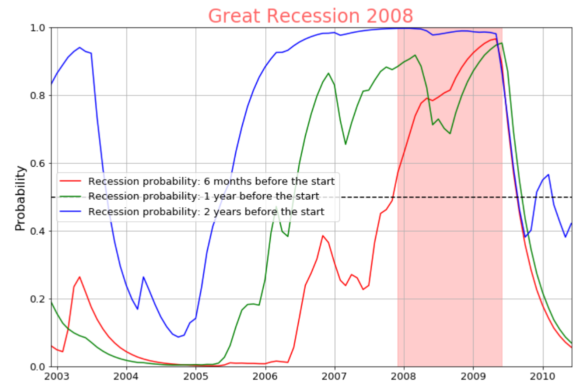
[11] D. E. Rumelhart, G. E. Hinton and R. J. Williams, “Learning Internal Representations by Error Propagation,” in Parallel distributed processing: explorations in the microstructure of cognition, vol. I, MIT Press, 1986, pp. 318–362.

[12] S. Hochreiter and J. Schmidhuber, “Long Short-term Memory,” Neural Computation, vol. 9(8), pp. 1735–1780, 1997.

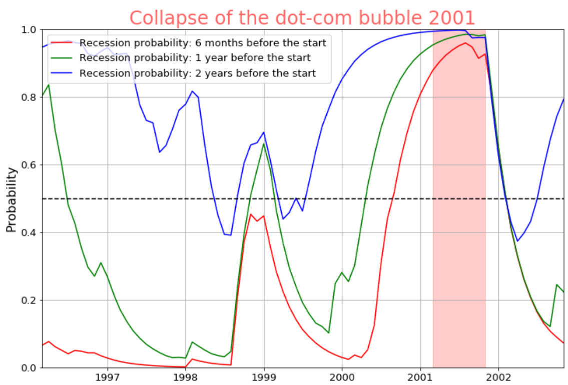
[13] T. Akiba, S. Sano, T. Yanase, T. Ohta and M. Koyama, “Optuna:A next-generation hyperparameter optimization framework,” in Proceedings of the 25rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. New York, NY, USA: Association for Computing Machinery, 2019, pp. 2623–2631.



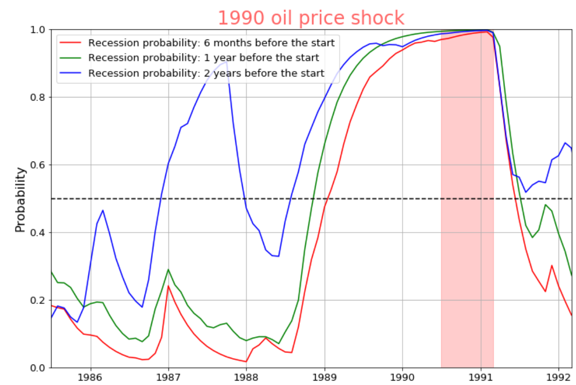

a) COVID-19 recession (02.2020 - 04.2020). Training period: 1955-2010, forecast period: 2010-2021.



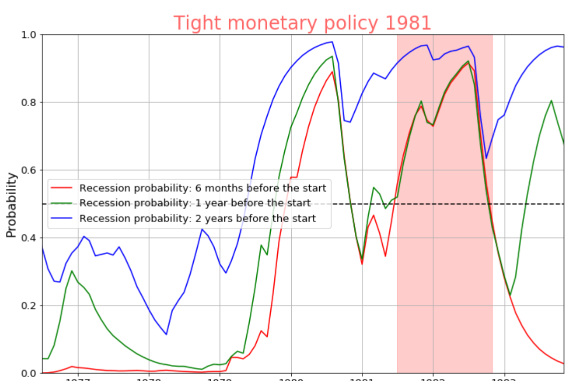

b) Great Recession (12.2007 - 06.2009). Training period: 1955-2003, forecast period: 2003-2010.



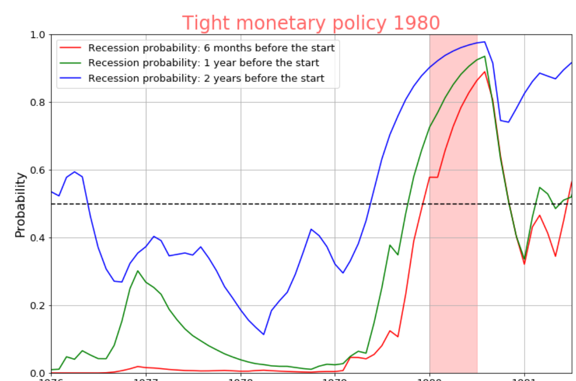

c) Collapse caused by the dot-com bubble (03.2001 - 11.2001). Training period: 1955-1993, forecast period: 1993-2003.




d) Early 1990s recession (07.1990 - 03.1991). Training period: 1955-1983, forecast period: 1983-1993.




e) Recession of 1981–82 (07.1981 - 11.1982). Training period: 1955-1981, forecast period: 1981-1983.




f) Early 1980s recession (01.1980 - 07.1980). Training period: 1955-1976, forecast period: 1976-1981.

Fig. 4. Six last recessions in the US economy from 1976 to 2021 (red areas on the charts) and their forecasting by three constructed indicators: red curve - the probability of the start of a recession within the next 6 months, green - 12 months, blue - 24 months.