NEURONET LOGISTIC DYNAMIC MODEL TO DIAGNOSE AND FORECAST THE STAGES OF DEVELOPING BANKRUPTCY OF CORPORATIONS

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Abstract

Purpose of Study: The object of the study is the problem of financial management, in particular, the problem of forecasting the stage of developing bankruptcy of corporations-loaners and decision-making on the restructuring of credit debt.

The subject of the research is the development of a dynamic model of bankruptcies with continuous time in conditions of high uncertainty and noise data, which allows diagnosing the stages of bankruptcy of the simulated object at any time (between the “time slices” in the data), as well as to predict the probability of bankruptcy in time ahead for a given horizon. Uncertainty is understood as a specific characteristic of the simulated class of dynamic bankruptcy problems – incompleteness and uncertainty in the data: in the training sample in the “time slices” only the boundary values of the probability of bankruptcy are specified (P=0 or P=1), i.e. there is no information about the intermediate values of P in the interval [0;1]. The uncertainty is determined by legal reasons: until the corporation is declared bankrupt by the arbitration court or the tax authorities, for it P=0, although objective accounting data may show proximity to bankruptcy.

Methodology: The purpose of the study is to create an effective mathematical tool for predicting corporate bankruptcy to support decision-making on the financial management of corporations, which is focused on complex real-world modeling conditions.

Results: On the basis of the system-wide law of inertia of the simulated dynamic system (or object), the original neuronet iterative logistic dynamic method (NLDM) is proposed, which allows eliminating the above incompleteness and uncertainty in the training sample and operate with continuous time in the procedures of diagnosis and prediction of bankruptcy stages of corporations-loaners. The adequacy of the dynamic model of bankruptcies is comprehensively investigated. The probability of correct identification of bankruptcies on the test set is not worse than 90%. The convergence of iterative procedures in the NLDM algorithm is investigated.

Keywords: Neural Network, Algorithm for Optimal Selection of Factors, Compression of Factors in the Clusters, Harrington Function, Dynamic Model of Bankruptcies, Model Regularization, Model Adequacy.

INTRODUCTION

The dynamic forecast model of assessment of stages of developing a process of the bankruptcy of corporations and companies is relevant, first of all, for decision-making on the restructuring of credit indebtedness in bank credit technologies. In a broader sense, this model is important as a tool for ensuring the economic security of corporations, a tool for monitoring and managing economic objects.

Modern diagnostics of the probability of bankruptcy acquires a special role in the unstable economic situation at the macro and micro levels. The study of empirical data revealed direct and indirect signs of developing bankruptcy. The main direct signs can be recognized:
• the critical level of liquidity of assets manifested in the excess of the organization’s obligations over current assets, as well as the negative dynamics of solvency indicators;
• the largest share in the composition of assets and capital accounts for receivables and payables;
• the significant excess value of the loan capital on their own;
• lack of own working capital and net current assets;
• the deterioration of business activity, associated with a decrease in sales volumes and overstocking, which led to an increase in costs, and as a consequence, the unprofitability of the corporation.

Indirect signs of the probability of bankruptcy can be such factors as the lack of capital investments in the modernization and reconstruction of production services, as well as reducing the cost of maintenance and operation of fixed assets; the adoption of unreasonable and ineffective management decisions; termination of business cooperation with the main contractors; reducing the share of influence on the market, etc.

In Russian and foreign practice, solvency and financial stability indicators are calculated to assess the risk of bankruptcy. In accordance with the guidelines for the analysis of the financial condition of organizations, these indicators are the first class indicators and have the appropriate regulatory values. Despite the fact that the analysis of indicators of solvency and financial stability is carried out in comparison with the data obtained in the dynamics and in comparison with the standards, it is not always possible to give an objective assessment. As the frequency of such reporting is 12 months, many other factors, including uncertainties of various kinds, unaccounted for in the reports, affect the receiving of reliable data.

With regard to the activities of modern financial and economic objects, in which there is the above uncertainty in the characteristics of these objects and the conditions of their functioning, the construction of a dynamic model of bankruptcies cannot be performed by known methods of diagnosis of bankruptcies: Altman’s Z-account, Beaver’s model, Taffler test, Savitskaya’s discriminant model, R-model of the Irkutsk State Economic Academy, the Saifullin-Kadykov’s medium-term rating forecast. To fend off the manifestations of uncertainty in the training set and in the process of object functioning is possible only in the adaptive (intelligent) model, the means of rapid adjustment of model parameters to changing the current situation. Intelligent neuronet methods are well suited here [Gorbatkov, Rastegaeva, Farhieva, Nakonechnaya, Shashkova (2018)].

However, the effective application of neuronet methods for building dynamic bankruptcy models directly to the original “raw” data is hardly possible. It is necessary to develop a formalized procedure for structuring the training sample and optional selection of factors, as well as their subsequent compression. Here is a quote from Tyumentsev Yu. (2017) “Obtaining a training set with the required level of information content is a critical step in solving the problem of building a neuronet model (NNM). If some features of the dynamics (behavior of the dynamic system) are not reflected in the training set, they will not be reproduced by the model”. In Gadzaov, Dzerzhinskaya (2018) this provision is formulated as the basic rule of identification: “It is impossible to identify what is not in the data”.

We mean that under informativity of data training set we will understand the requirement for adequate reflection in the ordered records

\[
(y_{g,t}; x_{g,t}), \ g \in \mathbb{G}; \ t \in [t_0, T]; \ x = (x_1, ..., x_j, ..., x_n) \in X
\]

patterns of “input-output” of simulated objects that need to be restored using the NNM. Here \(y_{g,t}\) – NNM output value for g-th object at time t; \(\hat{x}_{g,t}\) – the values of the vector of input factors on the model; \(t_0\) – initial time; \(T\) – the observation period in the formation of the data; \(X\) – the space of quantitative and qualitative factors. In addition to this requirement of “adequate reflection”, it is necessary to meet the requirement of the data sufficiency contained in the set for training and testing of the NNM, which with the required level of accuracy could reproduce the behavior of the dynamic system (DS) in the entire range of possible values for the simulated generalized characteristics – the probability of bankruptcy \(P[y(x(t))] \in [0; 1]\).

The questions of a selection of factors in the formation of training samples for dynamic NNM are poorly investigated, more precisely among several hundred works on bankruptcies, a review of which is given in [Beloliptsev, Gorbatkov, Romanov, Farkhieva, Gorbatkov, FarKhieva, Beloliptsev 2018], a theoretically sound general approach (concept) to the formation of factor space is not developed. The exception is the work of J. Rissanen [Rissanen, 1978] and S.A. Shumsky [Kuznetsov, Ignatyeva, Kuznetsov, 2018], where generalized important theoretical conclusion based on the Kullback-
Leibler information criterion is made: the shorter the total length of the data description and the model (and thus the number of variables in the model), the better generalizing ability of the NNM is, i.e., its predictive properties. From the point of view of this recommendation, it is rational in the initial expert-formed system of factors to make the optimal selection [Gorbatkov, Rastegaeva, Farhieva, Nakonechnaya, Shashkova, 2018], and then perform the operation of factor compression, if their number is too large, for example, more than 50.

An important and scantily explored issue of building a dynamic NNM of bankruptcies is the justification of the adequacy of the model and the regularization of its training in complex conditions of incomplete data and the lack of a priori information about the form of the noise distribution law in the measurement of the data. Here, the authors of the article consciously refuse to constrain the developed model with assumptions about any kind of noise distribution law, like [Kuznetsov, Ignatyeva, Kuznetsov 2018], which brings our model closer to practice.

The study of the above poorly studied issues of development of methods for building a dynamic model of bankruptcies in complex conditions of uncertainty of data served as a promise to the writing of this article.

The Research Task Setting

Let us consider in more detail the problem of data incompleteness and uncertainty specific to the problems of bankruptcies. Data are usually formed as “time slices” (1), in which
\[ t = t_1, t_2, \ldots, t_N, \]
where \( N \) is the number of slices during the observation period of each \( g \) – object of financial management. At the same time, as it was noted above, the boundary points of the range of possible values of the probability of bankruptcy of the corporation-loan are indicated in the time slices: \( P=1 \) (“bankrupt” corporation) and \( P=0 \) (“non-bankrupt” corporation). There is no information about intermediate values of \( P \) in the interval \([0; 1]\), which characterize different stages of the developing bankruptcy process. The incompleteness of data in time slices is related to the uncertainty caused by legal reasons: until the corporation is declared bankrupt by the arbitration court or tax authorities, for it the data indicate \( P = 0 \), despite the fact that the financial statements may show the proximity of the object to bankruptcy, for example \( P \in [,0.8; 1] \). In this case, in the model the artificial “asymmetry” is implemented: information on the bankruptcy of the corporation is reliable, but the information on the assignment of the label “non-bankrupt” \( (P=0) \) contains a high degree of uncertainty caused by the deformation of the model with legal features of the bankruptcy procedure.

In the formation of the training set for NN, there is a problem, which we called “dynamic data incompleteness”. Before the authors’ study, the solution to this problem was not considered. We emphasize that “dynamic data incompleteness” in NN training is one of the specific properties of the NNM as a data-driven model. The essence of this problem is as follows.

Let there be retrospective data of the form (1). In the last time slice \( (k=N) \), both the vectors of the factor values \( \bar{x}\_{zn} \), and the values of the output variable \( y = \arg \max \{P(\bar{x}\_{zn}, t_N)\} \) are usually known. This allows training the NN and estimate the probability of bankruptcy \( P \) in the last time slice \( (t=t_N) \). However, for some of the previous time slices \( (t_1, t_2, \ldots, t_{N-1}) \) the values of the output variable may be unknown, as by the time \( t \leq t_N \) in some of the corporations-loaners the crisis process is developing, and they are not recognized as bankrupt yet.

Hence there is a conclusion: regardless of the applied method of constructing a bankruptcy model, the negative manifestation of the noted incompleteness, uncertainty, and asymmetry of information in the data must be somehow eliminated, or at least significantly weakened. This conclusion formed the basic idea of the proposed iterative NLDM.

We present the information and mathematical formulation of the research problem. We consider the inverse problem (IP) of recovering the dependence of the probability of bankruptcy \( P \) on the vector of exogenous variables \( \bar{x}, h idden in the data. This dependence will be determined in the form of the logistic function proposed by Olson, 1980.

\[ P(t) = \frac{1}{1 + \exp \left( -\hat{y}(\bar{x}(t), t) \right)}, \quad P \in [0; 1]. \]  
(2)

The value of the exponential \( \hat{y}(\bar{x}(t), t) \) playing the role of argument in (2), is restored by using the neural network (NN) display of data:

\[ \hat{y}(\bar{x}, t) = F(\bar{x}, W, t); \quad F: \bar{x} \in \mathbb{R}^{(n)} \rightarrow \hat{y} \in \mathbb{R}^{(l)}, \]  
(3)

where \( W \) – many synaptic weights and biases in the neurons; \( F(\cdot) \) – the NN-display operator.
Let us note an important feature of the logistic function for building a dynamic NN model: the display (2) is compressive in the sense that the interval for the argument of the function \( \hat{y}(t, t) \in [-6; 6] \) is displayed in the corresponding interval of the value of the function \( P \in [0; 1] \), i.e. the compression ratio is approximately 1:12. Therefore, if NNM (2)–(3) has been received, tested and examined, errors in the assignment of the vector of factors \( \vec{x} \) will “shrink” by operator (2) for calculating the probability \( P \). However, for NNM (3) the learning objective of network, i.e., location \( W \) is IP, incorrectly set on Hadamard [Tikhonov, Arsenin, 1979], and therefore requires special measures for the regularization of the issue, which was noted in [Gorbatkov, Rastegaeva, Farhieva, Nakonechnaya, Shashkova (2018), Gorbatkov, Polupanov, Makeeva, Biryukov, 2012]. In this article on the basis of Bayesian approach the algorithm of regularization of statistical NNM is stated, which is also used by us in the considered dynamic model of bankruptcies.

The conceptual basis and neuronet logistic dynamic method of constructing a model of bankruptcies

As a conceptual basis as a methodological foundation for building a dynamic bankruptcy model, two concepts are developed:

**Concept 1:** The carrier of indirect, but sufficiently reliable information about the dynamics of the bankruptcy process in the financial management system, i.e. in a dedicated cluster of corporations-loaners, is a set of exogenous variables \( \{\vec{x}_t\} \), changing in time \( (t \in [t_1, t_N]) \). Moreover, the information \( \{\vec{x}_t\} \) is known in advance in all time slices of the data, i.e. it is complete.

**Concept 2:** Using the law of time inertia of financial management objects, it is possible to use specially constructed iterative procedures with the help of the neural network to extract knowledge about the process dynamics from the indirect information contained in the time slices of factors \( \{\vec{y}_t, t_k\}, k=1,2,...,N \), specified in concept 1, and to restore incomplete, uncertain and asymmetric information about the values of the endogenous variable \( \{\vec{y}_t, t_k\} \) in time slices.

Let us now consider a specific algorithm of NLDM, which implements concepts 1 and 2 and includes four subtasks:

A. Formalization and optimization of factors selected for the formation of the training sample.
B. Exploring opportunities for effective use in the construction of the NNM bankruptcies aggregating the generalized function of Harrington desirability (GFHD) [Gorbatkov, Rastegaeva, Farhieva, Nakonechnaya, Shashkova (2018), Adler, Markova, Granovsky].
C. Restoring incomplete, undefined, and asymmetric information about the values of endogenous variables \( \{\vec{y}_t, t_k\} \) in all time slices \( t_k = t_1, t_2, ..., t_N \).
D. Development of the algorithm of regularization of the ID decision of NN training, evaluation of the influence of aggregation factors in the form of GFHD in this algorithm.

The algorithm for solving the subtask A

Here the optimal selection of factors is carried out. An expert method is used to form a starting set of factors, i.e. “raw data” \( D \) is used to construct a Bayesian ensemble of auxiliary neural network submodels (ANNM), where – HN-hypotheses \( \{H_t(W, s)\} \) differ from each other by the type of activation function and the parameters of the structure \( s \) (the number of hidden layers of neurons and the optimal number of neurons in these layers). On the basis of ANNM the optimal selection of factors is made [Gorbatkov, Rastegaeva, Farhieva, Nakonechnaya, Shashkova (2018)].

The algorithm for solving the subtask B

The main process of complex (step-by-step) factor aggregation is carried out here. It differs from the known algorithms of factor compression by the fact that groups (clusters) of factors are firstly formed at the heuristic level on the functional economic basis, and then within each, \( u \) cluster the factors are aggregated in the form of GFHD [Adler, Markova, Granovsky] \( \{H_u\}; u = \frac{1}{M} \). and the NNM is built on the aggregated variables in (3):

\[
\hat{y}(H_u, t_k) = F(H_u, W, t_k), \quad k = \frac{1}{M}, \quad u = \frac{1}{M}.
\]
The algorithm for solving the subtask C

This subproblem of restoring of endogenous variables \( \{Y_{g}, t_{k}\} \) in time slices serves as the central core of the article. The algorithm of the iterative reconstruction process \( \{Y_{g}, t_{k}\} \) is arranged in steps:

**Step 1.** We introduce into the composition of factors, an additional factor – time \( t \equiv x_{n+1} \).

**Step 2.** We select the initial approximation \( \{Y_{g}, (t_{0}), \tilde{x}(t_{0}), t_{0}\} \) in the iterative process of iterating through all time slices of data \( (t_{k}=t_{0}, t_{1}, \ldots, t_{N}) \). In principle, any time slice from the data can be taken as an initial approximation if it contains information about the endogenous variable \( Y_{g, t_{k}} \), even though strongly noisy and deformed (asymmetric) (see section 1 of the article). It is convenient to choose the last slice with number N as a source of “fresh” information.

**Step 3.** On the set of records \( \{y, x_{g, N}\} \), the neural network with number \( N(\mathcal{H}C, N) \), is trained, let us call it conditionally “basic”, i.e. we realize neural network display [Haikin, 2006] of type (3).

**Step 4.** A hypothesis is put forward about the inertness of the dependence of \( y \) on the vector of factors \( \tilde{x} \) in the range between adjacent time slices \( k, k-1 \) according to the concepts 1 and 2 formulated above:

\[
F^{k-1}(\tilde{x}_{k-1}, W_{k}, s) \approx F^{k}(\tilde{x}_{k}, W_{k}, s) \Rightarrow \hat{y}_{k-1,g} \approx F^{k}(\tilde{x}_{g,k-1}, W_{k}, s),
\]

where \( F() \) – neural network display of view (3); \( k=N, N-2, \ldots, 1 \).

In other words, the network already trained and tested is used as a NNM for the slice \( k-1 \), which is obtained in the slice \( k = N \). Herewith

\[
W^{(k-1)} = W^{(k)}; \tilde{x}_{k-1} \neq \tilde{x}_{k}.
\]

Note: the sign of approximate equality in (5) means that the inheritance (due to inertia) of the NNM parameters \( W^{(k)} \) in the slice \( k-1 \) from the slice \( k \) introduces some error, which, as shown below, can be controlled and corrected:

\[
\varepsilon = \max_{y_{g,k-1}} |y_{g,k-1} - F^{(k)}(\tilde{x}_{g,k-1}, W_{k}, s)|; \varepsilon > 0.
\]

As a result of the search of all slices \( t_{k}=t_{N}, \ldots, 1 \) all endogenous variables \( \{\hat{y}_{g,k}\} \), \( k=N, N-2, \ldots, 1 \) are restored due to two mechanisms: the inertia of financial and economic objects in the transition from one time slice to another; the use of hidden (indirect) information about the dynamics of the bankruptcy process in the transition from one vector of factors \( \tilde{x}_{g,k} \) to another \( \tilde{x}_{g,k-1} \).

**Step 6.** After step 5, the database \( D \) increases by \( (N-1) \) times, i.e. its informativeness, as shown by computational experiments, grow.

An additional iterative process of error correction \( \varepsilon \) from (7) is organized. To do this, we construct a sequence of neural networks \( \{\text{NNM}(m)\} \) on the already complete data and recalculate the values \( \hat{y}_{g,k}^{(m)} \):

\[
\hat{y}_{g,k}^{(m)}(\tilde{x}_{g,k}) = F^{(m)}(\tilde{x}_{g,k}, W^{(m)}, s); m = 1, 2, \ldots, k, \ldots, N.
\]

Note. With high requirements for the quality of the forecast, it is possible to organize several runs on the index \( m \) in (8).

**Step 7.** The criterion for stopping the correction iterations \( \varepsilon \) of (7) - (8) is the condition of stabilization of the recovered values \( \hat{y}_{g,k}^{(m)} \):

\[
I^{(m)} = \max_{\vec{m} \in \mathbb{N}} \left\{ \max_{\vec{m} \in \mathbb{N}} \left[ \frac{y_{g,k}^{(m)}(\tilde{x}_{g,k}) - y_{g,k}^{(m-1)}(\tilde{x}_{g,k})}{y_{g,k}^{(m)}(\tilde{x}_{g,k})} \right] \right\} \leq \xi,
\]

where \( m=1,2, \ldots, N \). In practice, 1...2 forward-backward runs in (9) are usually sufficient.

**The algorithm for solving the subtask D**

In fact, the quasi-Bayesian regularization algorithm (QBRA) of the ID solution for finding the NNM parameters, i.e. the set \( W \), as described in Gorbatkov, Rastegaeva, Farhieva, Nakonechnaya, Shashkova (2018). It remains to formulate the idea of QBRA and to concretize its novelty.
QBRA uses the same paradigm of ID regularization as in Tikhonov’s theory [Tikhonov, Arsenin, 1979]. It is a narrowing of the space of the sought solutions $Z' \subset Z$, where $Z'$ is some “compact”. However, the method of narrowing $Z$ to the compact $Z'$ in QBRA is different from the construction of Tikhonov stabilizers:

- Due to the mechanism of a posteriori filtering of neural networks – $\{h_q\}$ hypotheses on the Bayesian ensemble and subsequent averaging of the model characteristics on the filtered ensemble.
- Due to the optimal selection of factors and their aggregation in the subtasks A and B.

**Quantitative assessments results**

First, we indicate the general points of the organization of computational experiments. As the initial data $D$, we used the retrospective data of corporations-loaners of one of the most common sectors of the economy – the construction industry, obtained by “Bereua Van Dijk” firm [Makeeva, Neretina, 2013]. The database contained 136 observations. A system of 15 specific indicators widely used in bankruptcy assessment tasks was used [Shevchenko, Khalafyan, Vasilyeva, Yu, (2010)]. The calculation of these specific indicators is contained in [Beloliptsev, Gorbatkov, Romanov, Farkhieva] according to the standard financial statements. An algorithm of Gorbatkov, Rastegaeva, Farhieva, Nakonechnaya, Shashkova (2018) optimal selection of factors with the use of regularization on the Bayesian ensemble in the ANNM was implemented.

**Estimation of convergence of iterative processes of endogenous variables restoration and correction of restored values**

For the proposed NLDM, the construction of a dynamic bankruptcy model, the question of convergence of iterative processes (5) - (9) is central. These estimates of the convergence of these processes are shown in Fig.1.

$\Theta$ quality criterion is expressed in a direct way through errors of corporate bankruptcy identification in the data:

$$\Theta_q = \frac{(N^{(\text{I})} / N) + (N^{(\text{II})} / N)}{\frac{1}{N} \sum_{q=1}^{Q^*} \Theta_q}$$

where $\bar{\Theta}$ – the average for the filtered on Bayesian ensemble criterion $\Theta_q$; $N$ – the total number of corporations-loaners in the original sample $\{(x_i, y_i)\}_{i=1}^{N}$; $G = \sum_{i=1}^{N} (N^{(\text{I})} / N^{(\text{II})})$ – the number of errors of the first and second kind in the identification of the probability of bankruptcy $P$ trained and tested with neural network presented examples throughout the sample; $Q^*$ – the number of NNM on the filtered Bayesian ensemble.

From Fig. 1 it can be seen that the recurrent iterative process (4) of reconstruction of endogenous variables $\{f_{q,k}\}$ at the motion from the time slice $k=5$ to the slice $k=3$ leads to the improvement of the quality criterion (10) from $\bar{\Theta} = 0.2417$ to 0.05, i.e. by 4.83 times. Consequently, the quality of restoration of endogenous variables $\{f_{q,k}\}$ by the finish criterion $\bar{\Theta}$ of (10) is very high.

Subsequent iterations $m = 4, 5$ and $6$ in Fig. 1 correspond to the correction process $\varepsilon$ by (7) - (9). Here, the convergence is oscillatory with a discrepancy between the steps not exceeding 0.0276. The reason for the fluctuation $\Delta\bar{\Theta}$ the discrepancy with small deviations of the order of 2.76%, the authors consider the “best” noise of the training data sample.

![Figure 1. Changing the quality criterion $\Theta$ identifying objects by steps $k$ of the process (5)-(6) and by steps $m$ of the process (7)-(9)](image)
Thus, computational experiments on the convergence of the restoration process of endogenous variables (5)-(6) and their further correction (7) - (9) confirmed the efficiency of the proposed concepts 1 and 2 of the construction of NLDM bankruptcies.

Estimates of the change in the probability of bankruptcy $P$ in time $t$, calculated by NLDM for 8 construction companies according to [Makeeva, Neretina, 2013], are shown in Fig.2.

Here, 2013 is a forecast year. It is seen that the dynamic model of bankruptcy, built on the NLDM, provides valuable predictive information for management decisions on financial management. Thus, JSC “PIK Group of companies” and JSC “Kazantsentstroy” have positive dynamics due to anti-crisis measures: the forecasted values of the probability of bankruptcy $P$ from the value of 0.98 decreased to (0.40,...,0.45). For other corporations, the forecast gives unfavorable values ($P > 0.56,...,0.76$), this indicates the ineffectiveness of anti-crisis measures taken in these corporations from 2009 to 2012.

Comparison of NLDM with known methods and techniques

The results of the assessment of bankruptcy stages obtained by NLDM for data from [Makeeva, Neretina, 2013] were compared with the calculations of 22 known statistical models of bankruptcies from [Gorbatkov, FarKhieva, Beloliptsev 2018, Olkhovskiy, 2018; Altman, 2007] for a cluster of 8 corporations in the construction industry. General conclusion in comparison: the known statistical methods and techniques do not have sufficient sensitivity to the signs of the developing process of the crisis in corporations, i.e. they do not allow obtaining a forecast for the time of the probability of bankruptcy $P(t)$. The proposed NLDM provides such a forecast (Fig.2).

CONCLUSION

1. With regard to the complex modeling conditions typical for bankruptcy problems, in which, in addition to the usual data noise, there are specific properties of uncertainty (asymmetry) and incompleteness of data, the construction of a dynamic bankruptcy model using traditional methods of econometrics is problematic. Here the application of intelligent neural network modeling methods is promising.

2. The conceptual basis and the original iterative neuronet logistic dynamic method (NLDM) for constructing bankruptcy models are developed. The main idea of this method is to use indirect information about all the nuances of the dynamics of the developing bankruptcy process contained in the values of the factors vectors $\mathbf{x}^t$ of the “time slices” of data. In this case, NLDM in the process of building a model restores incomplete data in slices and corrects their asymmetry.

3. By comparison with the estimates on 22 known statistical methods, including modern “advanced” logistics methods, it is shown that the NLDM has sufficient contrast, i.e. is able to differentiate the nature of the dynamic dependencies $P(\mathbf{x}(t), t)$ of the probability of bankruptcy. For credit institutions, this allows the lender tracking the dynamics of $P(\mathbf{x}(t), t)$ at servicing the loan portfolio and starting the debt restructuring procedure in a timely manner. 21 mentioned methods and techniques, in addition to the model [Altman 2007; Tabatabaei, Karahroudi, & Bagheri, (2014); Hojati,
mostly cover the current arsenal of models of risk of the bankruptcy, do not possess such a property of the contrast estimates. Consequently, NLMD expands the capabilities of modern economic and mathematical tools.

4. The authors see the direction of further research in the study of such a predictive model of bankruptcies for another mass sector of the economy – commercial enterprises, as well as the introduction of qualitative factors into the model of bankruptcy, taking into account the “cross-country effects”.

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