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MODELLING OF THE BANK'S CLIENTS' BEHAVIOR IN CASE OF OVERDUE DEBT

The article considers the methodological approach to the categorization of quantitative variables in the process of building scoring models as a mechanism for streamlining and dividing the consumer of the banking product according to their level of creditworthiness. This approach allows us to find the best ratio of the minimum group size by the criterion of maximizing the informational significance of indicators. The gradient boosting algorithm was used to assess the client's behaviour in the event of overdue debt in the next 30 days. This method involves the sequential construction of models in which every new model is learned based on information about the mistakes made in the previous stage. The resulting function is a linear combination of the whole ensemble of models considering the minimization of deviations. This approach makes it possible to obtain high efficiency on large data sets.

Key words: scoring, creditworthiness, gradient boosting, binning, Weight Of Evidence, Information Value, AUROC, classification, identification

Problem statement. In the banking sector, credit operations have a high level of profitability because the current dynamic market environment requires businesses to have additional funds to ensure the proper level of their operation. The high level of profitability causes a high level of risk of such operations, which leads to the creation of additional reserves. In this situation, the banking institution carries out fewer active operations, which is reflected in the level of its profitability.

Determining the borrower's creditworthiness for each banking institution is one of the main means of credit risk management. Existing methods of assessing the borrower's creditworthiness used by banks are improved and adapted to today's realities. They are a good filter to weed out insolvent customers. Such methods are based on scoring, discriminant analysis, and analysis by artificial intelligence methods. However, there are situations when the borrower is unable to repay the obligations in time due to bad faith performance of contractual terms by the counterparties, force majeure, personal reasons. Some borrowers will try to repay overdue debts, some will not fulfil their obligations. This begs the question – which of the debtors will continue to meet their credit commitments soon?

Analysis of recent research and publications. Many researchers are engaged in the study of assessing the creditworthiness of bank borrowers. V.Vitlinskyi, V.Vovk, O.Vasiurenko, O.Pernarivskyi, E.Gill, R.Kotter, M.Holzberg made a significant contribution to the disclosure of the essence of the bank's credit policy. Economic and mathematical tools for assessing creditworthiness are described in the works of G.Velykoivanenko[1],

[1] Великоіваненко, Г. І., Трокоз, Л. О. (2013). Моделювання кредитоспроможності позичальників комерційного банку. *Науковий журнал «Наукові записки Національного університету Острозька академія. Серія Економіка, 22, 137-141.*

A.Matviychuk[1], T.Smoleva[2], O.Hrygorovych[3], L.Thomas[4], R.Zenzerovych[5], H. Abdu[6], S. Akkok[7] and others. In most cases, scientists use scoring models allowing to assess the credit risks of the lender based on the calculation of quantitative indicators and qualitative characteristics of the borrower. Quite often, they are used in combination with methods of artificial intelligence allowing to obtain a new level of quality assessment. However, the study of the client's behaviour after the overdue debt occurrence needs further attention.

The purpose of this article is to determine which clients with a debt overdue will continue to repay the debt on the loan within the next 30 days. The main tasks are to study approaches to assessing the creditworthiness of borrowers and assess their further behaviour in case of overdue debt with the help of economic and mathematical tools.

Results and discussion. Banking institutions are interested in anticipating the ability and willingness of the client to repay the borrowed funds in accordance with the terms of the loan agreement, as well as in assessing the validity and appropriateness of credit investments and further relations with the borrower in the field of lending. In this regard, there are quite a number of approaches to modelling and assessing the creditworthiness of borrowers, developed by both foreign and domestic researchers, banks, and government regulators of the credit market.

Our study is based on scoring models as a tool for credit risk management. Scoring is an effective mechanism for ordering and dividing the consumer product of a banking product according to the level of creditworthiness on the basis of sets of qualitative and quantitative information about people, credit, and other factors that may indirectly affect compliance with credit obligations.

Various indicators are used to carry out the scoring assessment such as socio-demographic, professional-qualification, behavioural, etc. Accordingly, there are different types of scoring models: Application-scoring, Fraud-scoring, Behavioural-scoring. A special place is occupied by Behavioural-scoring which assesses the probable financial actions of the borrower, helps to make a forecast of changes in solvency based on human actions over a period. As a basis, there is a check of operational actions on the credit card before obtaining a loan. When using the system, an employee of a financial institution enters data on a specific person in the database, which issues a scoring score. Based on this indicator, a decision is made on whether it is possible to issue funds to the borrower[8].

The use of a behavioural scoring system makes it possible to assess all the benefits of systemic and high degree of automation of the process of working with each client of the credit institution. Behavioural scoring allows you to optimize time and labour costs, stabilize the loan portfolio, minimize the "human" factor in the decision-making process, as well as significantly increase the efficiency of risk management of the bank[9].

Basing on this method and gradient boosting algorithm, we simulate the situation regarding the borrower's behaviour in case of overdue debt.

The set of available qualitative and quantitative information about borrowers requires the categorization of indicators, namely the determination of the optimal number of categories and their ranges for each

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[1] Матвійчук, А. В. (2011). *Штучний інтелект в економіці: нейронні мережі, нечітка логіка*. Київ.
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of the quantitative explanatory variables, i.e. binning. The methodological approach to the categorization of quantitative variables in the process of building scoring models involves the following steps[1]:

1) collection of information base, formation of training and test samples;
2) division of sets of values of explanatory variables into categories according to binning algorithms;
3) calculation for each category for all variants of binning indicators *WOE (English Weight Of Evidence)* and *IV (English Information Value)*;
4) construction of scoring models on the training sample for different options for categorization of input variables;
5) assessment of the adequacy of the constructed scoring models on the test sample according to the *AUROC* (*Area Under Receiver Operating Characteristic*) criterion;
6) analysis of the obtained results, formulation of conclusions on the effectiveness of binning algorithms.

A data set of a banking institution with the characteristics of existing customers who use or have used the loan service has been obtained to build a mathematical model. The data set consists of 219,075 observations of 118,909 bank customers. Each observation contains 145 factors and the dependent variable *pay*. The dependent variable *pay* is a binary value that indicates the event/fact of repayment by the borrower of the debt in the next 30 days (becomes "1") and non-fulfilment of contractual terms (the value of "0"). The structure of the input sample according to the dependent variable is as follows:

Table 1

The structure of the input sample

Name	Value «0»	Value «1»
Number of records, units	80 400	138 675
Share, %	0,367	0,633

Training and test samples for the model at each iteration are formed randomly in the proportion of 70/30 while maintaining the initial ratio of the classes of the resulting indicator. In our case, the distribution of training and test samples is in the form of Table 2 and Table 3.

Table 2

Training sample for model construction

Name	Value «0»	Value «1»
Number of records, units	56 434	96 918
Share, %	0,368	0,632

Table 3

Test sample for model quality validation

Name	Value «0»	Value «1»
Number of records, units	23 989	41 734
Share, %	0,365	0,635

It should be noted that the data contain gaps and require prior preparation. The replacement of existing passes was carried out using the method of the nearest neighbour (knnImpute[2]). This approach to filling in the missing values in the sample allows you to save observations and make a prediction based on machine learning rather than a simple replacement such as medium or fashion.

[1] Клебан, Ю.В. (2019). Дослідження способів трансформації даних в контексті підвищення ефективності моделей кредитного скорингу. *Нейронечіткі технології моделювання в економіці. Науково-аналітичний журнал, 8,* 94-123.
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It is necessary to transform explanatory variables for their effective application before building mathematical models. All indicators are categorized with the calculation of the corresponding[1]:

- Weight of Evidence (WOE)

$$WOE_i = ln\left(\frac{B_i}{G_i}\right), i = \overline{1,k}, \tag{1}$$

Bi – the ratio of the number of unreliable borrowers in the *i* category to the number of unreliable borrowers in the sample; *Gi* – the share of reliable transactions in the *i* category in relation to their total number; *k* is the number of subgroups (categories) of the variable.

WOE is calculated for different categories of qualitative indicator or intervals of quantitative indicator and for a separate category corresponding to the missed data, in particular. Thus, the use of WOE provides an opportunity to make the model universal, i.e. one that can be used for any filling of data on the characteristics of borrowers. In addition, the calculation of WOE translates qualitative and quantitative indicators of different dimensions to normalized numerical values suitable for building scoring models of any type.

- Information Value (IV)

$$IV = \sum_{i=1}^{k}(B_i - G_i) \cdot WOE_i. \tag{2}$$

The value of the information significance indicator indicates the level of connection of the original variable with the predictor. The higher the information value of the predictor, the stronger the dependence of the original variable on it. The coefficients IV obtained as a result of calculation (2) are interpreted as follows: IV <0,02 – the characteristic has no prognostic force; 0.02 ≤ IV <0.1 – weak prognostic force; 0.1 ≤ IV <0.3 – average prognostic force; 0.3 ≤ IV <0.5 – high prognostic force; 0.5 ≤ IV – excellent predictive power of the categorized variable.

The binning procedure for qualitative indicators is quite simple and involves assigning them to categories with corresponding quantitative WOE values. The following algorithm is used for quantitative indicators[2]:

– formation of a training sample and setting the minimum size of the category;

– combining adjacent elements with zero values; grouping of the extreme "upper" and extreme "lower" groups separately with the corresponding calculation for them WOE and IV;

– aggregation of the remaining categories towards the middle of the whole set of values of the indicator;

– in case the newly formed categories do not correspond to the already set trend of the WOE indicator, they are combined with the previous / next categories according to the proximity of the WOE.

This algorithm allows you to find the best ratio of the minimum group size by the criterion of maximizing the informational significance of indicators.

As a result of construction of scoring models on the basis of various algorithms, the indicators having the greatest specific weight for the solution of the set task were selected, namely: marital status, total net income, assets, term of residence in one place, age of a client, liquidity group, its availability, area of employment and length of service, the percentage of arrears on all previous loans of the total, overdue payments on the loan, the number of services used by a client, as well as the frequency of communication between a client and a bank (number of calls).

The resulting indicator of the scoring model, which indicates the probability of repayment by the debtor of overdue debt within the next 30 days, is the actual number determined in the interval [0; 1]. Besides, at the final stage of forecasting, a “cut-off” line is calculated, which determines the division of customers into classes "reliable" / "unreliable" using the conditions:

✓ If the probability of debt repayment within the next 30 days is less than the value of the “cut-off” line, the client is considered "unreliable" *predicted_prob <cuf_off, then pay = 0*). A bank should work with such clients in the first place.

[1] Клебан, Ю. В. (2019). Дослідження способів трансформації даних в контексті підвищення ефективності моделей кредитного скорингу. *Нейронечіткі технології моделювання в економіці. Науково-аналітичний журнал, 8,* 94-123.
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✓ If the probability of debt repayment within the next 30 days is greater than or equal to the value of the "cut-off" line, the client is considered "reliable" (*predicted_prob> = cuf_off, then pay = 1*). A bank should work with such clients in the second place.

The evaluation of the quality of the constructed mathematical models was carried out on the data of the test sample, which was not used in the construction and training of models. *AUROC* was used as an indicator to compare the models, which is a classic characteristic for assessing the accuracy of binary classification.

The best *AUROC* result on the test sample was obtained using the model based on *eXtreme Gradient Boosting (xgboost)*. The algorithm by this method involves the formation of the input data stream *Data Set D*, the loss function L, the number of iterations M, the learning rate η and the number of completed nodes T[1]:

- Performing initialization $\widehat{f_0}(x) = \sum_{i=1}^{n} L(y_i, \theta)$ for $m = 1,2, \dots, M$ we find the fastest deviations (risks)

$$\widehat{g_m}(x_i) = \left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]_{f(x)=\hat{f}^{(m-1)}(x)} . \quad (1)$$

- Determine the risk structure $\{\hat{R}_{jm}\}_{j=1}^{T}$ selecting the deviations that maximize

$$Gain = \frac{1}{2}\left[\frac{G_L^2}{n_L} + \frac{G_R^2}{n_R} - \frac{G_{jm}^2}{n_{jm}}\right]. \quad (2)$$

- Determine the weight of the constituent elements $\{\widehat{w}_{jm}\}_{j=1}^{T}$ for the studied structure

$$\widehat{w}_{jm} = \arg min_{wj} \sum_{i \in \hat{I}_{jm}} L(y_i, f^{(m-1)}(x_i) + w_j. \quad (3)$$

Lower weights of the constituent elements will give models that are closer to the overall constant, while larger coefficients will give more complex models.

- Turn on the learning speed indicator η

$$\hat{f}_m(x) = \eta \sum_{j=1}^{T} \widehat{w}_{jm} I(x_i \epsilon \hat{R}_{jm}) \quad (4)$$

If η is set too high, the model will fit most of the structure into the data during early iterations, thereby rapidly increasing the variance. By reducing the learning rate η, we can add more trees before the additive tree model begins to overload the data. This will allow the model to have greater representativeness.

- Combining the above, for each iteration *m* gives a "step"

$$\hat{f}^{(m)}(x) = \hat{f}^{(m-1)}(x) + \hat{f}_m(x) \quad (5)$$

- As a result, we get a model based on eXtreme Gradient Boosting

$$\hat{f}(x) \equiv \hat{f}^{(\mathrm{M})}(x) = \sum_{m=0}^{M} \hat{f}_m(x). \quad (6)$$

Several indicators were used to determine the effectiveness of the proposed model, in particular, a ROC curve was constructed. This curve evaluates the correctness of the binary classification. The ordinate axis reflects the proportion of correctly determined positive TPR results (True Positive Rate), the abscissa axis – the proportion of misdiagnosed positive FPR results (False Positive Rate) when varying the cut-off threshold[2]. Visualization of the obtained results is presented in Fig.1 and Fig. 2.

[1] Nielsen, D. (2016). *Tree Boosting with XGBoost. Norwegian University of Science and Technology* <https://ntnuopen.ntnu.no/ntnu-mlui/bitstream/handle/11250/2433761/16128_FULLTEXT.pdf?sequence=1&isAllowed=y> (2020, November, 23).

[2] Клебан, Ю. В. (2019). Дослідження способів трансформації даних в контексті підвищення ефективності моделей кредитного скорингу. *Нейронечіткі технології моделювання в економіці. Науково-аналітичний журнал, 8,* 94-123.

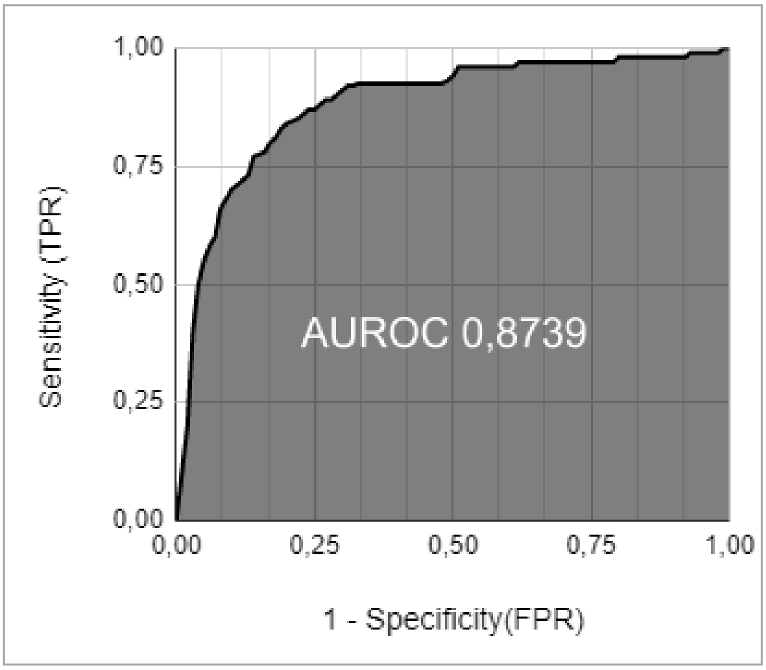

Fig. 1. ROC-curve of the constructed model for assessing the behaviour of consumers of credit services in the training sample

Source: compiled by the authors.

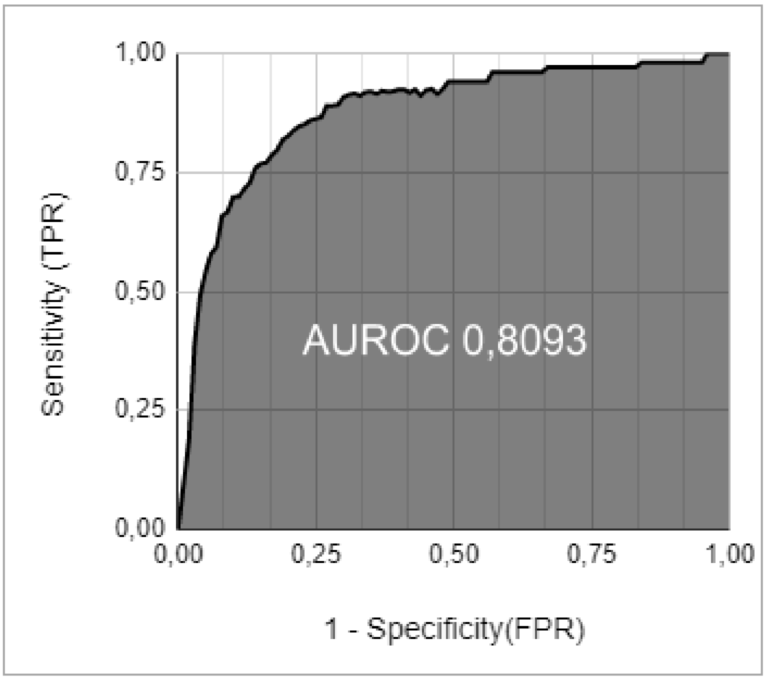

Fig. 2. ROC-curve of the constructed model for assessing the behaviour of consumers of credit services in the test sample

Source: compiled by the authors.

Assessing the overall accuracy of the classification, the cut-off line was set at 0.49, which made it possible to calculate the following indicators:

– Gini coefficient, as an indicator of the distribution of inequality of some value, for the training sample became important

$$\text{Gini (train)} = 2 * \text{AUROC} - 1 = 0.7478; \text{ for test sample} - \text{Gini (test)} = 0.6186.$$

– assessment of the balanced classification accuracy, taking into account the proportions of positive and negative events in the sample Balanced Accuracy:

Table 4

Performance indicators of the customer classification model in the test sample

Accuracy	Sensitivity	Specificity	Prevalence	**Balanced Accuracy**
0.7489	0.7801	0.6810	0.6853	**0.7305**

The obtained simulation results made it possible to construct the final distribution of clients from the test sample by percentiles with a range of 10% (Table 5).

Table 5

Comparison of the actual and projected probability of loan repayment within 30 days by clients included in the test sample

Range	Number of customers who paid the debt	Number of customers who did not pay the debt	The share of customers who paid the debt	The share of customers who did not pay the debt
0,9 - 1	10283	625	24,64%	2,60%
0,8 - 0,9	10169	1692	24,37%	7,05%
0,7 - 0,8	6350	2031	15,21%	8,46%
0,6 - 0,7	4242	2252	10,17%	9,39%
0,5 - 0,6	3730	2951	8,94%	12,30%
0,4 - 0,5	3330	4066	7,98%	16,95%
0,3- 0,4	2128	4077	5,10%	17,00%
0,2 -0,3	1035	3158	2,48%	13,16%
0,1 - 0,2	372	2029	0,89%	8,46%
0 - 0,1	95	1109	0,23%	4,62%
Total:	***41734***	***23989***		

Source: compiled by the authors.

The table shows that in the range of probabilities 0.8 – 0.9 (80% – 90%), calculated by the model, got only 10169 + 1692 = 11861 clients. Here 10,169 are the customers who have paid the amount within the specified period of 30 days, which is 24.37% of those who have repaid the debt.

Approximately 65% of all customers who have deposited funds are in the range with a probability of 0.7-1 (more than 70%).

Conclusions. The analysis of scientific works of famous scientists and the experimental approach to solving the problem has allowed to form an algorithm for assessing the behaviour of a bank’s client with an overdue debt. The high efficiency of the obtained simulation results indicates the need to apply such technology in practice to reduce the level of credit risk of the banking institution.

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