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ABOUT ONE APPROACH TO THE FORMAL ASSESSMENT FOR THE QUALIFICATION OF COMMERCIAL BANK CREDIT ANALYSTS

ПРО ОДИН ПІДХІД ДО ФОРМАЛЬНОГО ОЦІНЮВАННЯ КВАЛІФІКАЦІЇ КРЕДИТНИХ АНАЛІТИКІВ КОМЕРЦІЙНОГО БАНКУ

Non-effective credit management can lead to significant losses and even bankruptcy of a bank. Therefore, in order to minimize possible losses, bank specialists should assess the creditworthiness of a potential borrower at a high level. This fact and the high competition of banks has led to the widespread use of scoring systems. At the same time, there is no universal scoring model, and the automated system cannot detect suspicious behavior or a borderline state of the client. Thus, to make a credit decision, it is advisable to rely not only on the results of the scoring system, but also on the opinion of qualified experts (credit analysts), which is especially important when the economic situation changes. Therefore, the formal scheme of assessing the qualifications of a credit analyst based on available a priori information is relevant. In accordance with the proposed approach to assessing credit histories, analysts use their testing based on previously identified results of the analysis of credit histories in banks. The tested candidates have to assign former bank borrowers to one of two classes – a trustworthy borrower who easily fulfills the terms of the loan, or an unreliable borrower who repaid the loan by force. If, according to the test results, the average risk of a credit analyst decisions is less than the decisions a priori risk that a bank manager makes only on the knowledge basis for the probabilities of the reliable and unreliable clients appearance, then the credit analyst is considered qualified. In addition, a scheme for selecting the most qualified credit analysts in the credit decision-making group based on the proposed formal conditions is provided. For practical application of the proposed approach, it is sufficient to assess the a priori probabilities of reliable and unreliable customers in the test sample of credit histories and conditional probabilities of errors made by a potential credit analyst in classifying customers of a bank with a known credit history. A model example illustrating the proposed approach is given.

Keywords: *credit analyst, scoring system, classification the risk of a potential borrower.*

Неефективне управління у сфері кредитування може призвести до суттєвих втрат і навіть банкрутства банку. Отже, для мінімізації можливих втрат фахівці банку мають провести кредитну оцінку платоспроможності потенційного позичальника на високому рівні. Цей факт і висока конкуренція банків у цій сфері призвела до широкого застосування скоринг систем. Водночас немає універсальної моделі кредитного скорингу і автоматизована система неспроможна зафіксувати підозрілу поведінку чи граничний стан клієнта. Таким чином, при прийнятті кредитного рішення доцільно спиратися не тільки на результати скоринг системи, але й на думку кваліфікованих експертів (кредитних аналітиків), що особливо важливо при зміні економічної ситуації. Тому побудована на байєсовських стратегіях класифікації формальна схема оцінки кваліфікації кредитного аналітика на основі наявної апріорної інформації є актуальною. Відповідно до запропонованого підходу для оцінки кваліфікації кредитних аналітиків проводиться їх тестування, використовуючи раніше відомі результати кредитних історій банку. Кандидату необхідно класифікувати колишніх позичальників банку, відносячи їх до одного з двох класів – благонадійний позичальник, який без проблем виконав умови кредитування або неблагонадійний позичальник, який повернув кредит у примусовому порядку. Якщо за результатами тесту середній ризик рішень кредитного аналітика менший за апріорний ризик рішень, які менеджер банку приймає лише на підставі знання ймовірностей появи благонадійних та неблагонадійних клієнтів, то кредитний аналітик вважається кваліфікованим. Також у статті наведено схему вибору найбільш кваліфікованих кредитних аналітиків у групу прийняття кредитного рішення на основі запропонованих формальних умов. Для практичного використання запропонованого підходу достатньо оцінити апріорні ймовірності благонадійних та неблагонадійних клієнтів у тестовій вибірці кредитних історій та умовні ймовірності помилок, які допускає потенційний кредитний аналітик при класифікації клієнтів банку з відомою кредитною історією. Надано модельний приклад, що ілюструє запропонований підхід.

Ключові слова: *кредитний аналітик, скорінг системи, риск класифікації потенційного позичальника.*

Introduction. It is known that bank loans, which bring the main income of a commercial bank, with inefficient management, can lead to significant losses and even bankruptcy of the bank.

To minimize possible losses, before issuing a loan, bank specialists conduct a credit assessment of the solvency of a potential borrower, which often consists in comparing the client's characteristics with other clients of an earlier period. A loan application will only be granted if the client's characteristics satisfactorily match those who have not defaulted. To assess the creditworthiness of a client, there are two approaches: using a scoring system and based on the assessment of a credit analyst.

Each of the approaches has its own advantages and disadvantages.

Since the high competition of banks in the field of lending leads to the need to formalize the processes of making credit decisions, automated systems for the formation of credit decisions (the so-called scoring systems) are now quite widespread, which, with a certain degree of certainty, are able to classify cus-tomers into reliable and unreliable [1; 2].

According to [3], the classification of the applicant is based on such characteristics as gender, age, marital status, education level, loan amount, loan term, real estate, monthly income, as well as similar characteristics of the personal information of the spouse of the potential borrower.

At the same time, as rightly stated in [4], there is still no universal credit scoring model. In addition, sometimes scoring systems classify the borrower as reliable, while bank experts note that his demeanor, appearance, and emotional state are suspicious.

It follows that for making a credit decision, it is advisable to take into account not only the results of the scoring system classification but also rely on the opinion of qualified experts (credit analysts), which is especially important when the economic situation changes [4; 5].

The task of a credit analyst is to evaluate, based on the characteristics of the client and his knowledge, intuition, the solvency of the client. That is, the main task of a credit analyst specialist is to minimize the risk of loan default. Although it is believed that the opinion of a credit analyst can be subjective, and computer-scoring systems make a formal decision on issuing a loan, recently a large number of scientific publications have been devoted to the integration of scoring systems and the knowledge of credit analysts [5]. The task of selecting qualified experts for the group is also relevant [6].

The term "qualified" expert is quite common in publications, including scientific literature. Intuitive definition of such a term is clear: a qualified expert is a recognized specialist in a particular subject area. However, the assessment of the qualifications of credit analysts requires the formalization of an individual expert the knowledge.

The qualification of a credit analyst can be integrally characterized by the probabilities (frequency) of his mistakes made in assessing the creditworthiness of a client. At the same time, erroneous decisions of an expert can be of two types: recognizing an unreliable client as creditworthy and vice versa refusing to issue a loan to a trustworthy potential borrower.

Since, in the general case, the material losses of a commercial bank from such errors are different, it is reasonable, as is customary in statistical classification methods, to evaluate the qualifications of a credit analyst in the framework of Bayesian strategies. In other words, to characterize the classifications of credit analysts in terms of the average losses of their decisions [7].

Formulation of the problem. The purpose of the article is to build a formal scheme that allows, based on the available a priori information, to assess the qualifications of a credit analyst and to select the most qualified credit analysts.

Methodology. For the study, the apparatus of probability theory, mathematical statistics and methods of the statistical decision theory (Bayesian classification strategy) were used.

Research results. For building a credit analysts group, potential candidates are tested. The data of the bank's credit flows are used for evaluation. The tested candidate is asked to classify the bank's former borrowers into one of two classes – a trustworthy borrower who fulfilled the loan conditions without problems (class V_1) or an unreliable borrower who repaid the loan by force (class V_2).

The tested candidate, based on the available information of credit histories and his intuition, makes decisions about the reliability of the client in the form of an indicator variable

$$\delta = \begin{cases} 1, & \text{if the expert decides in favor } V_1, \\ 2, & \text{if the expert decides in favor } V_2, \end{cases} \tag{1}$$

It is assumed that when classifying clients, in addition to the correct ones, erroneous decisions can be made: a trustworthy client is assigned to the class V_2 or an unreliable client – to the class V_1, i.e. errors of the first and second kind are allowed [7].

In accordance with the statistical decisions theory, possible solutions are characterized by the payoff matrix

$$L = \begin{pmatrix} L_{11} & L_{12} \\ L_{21} & L_{22} \end{pmatrix} , \tag{2}$$

where L_{11} and L_{22} – losses associated with the right decisions, L_{12} and L_{21} – losses associated with mistakes to recognize a trustworthy client as untrustworthy and vice versa.

Then the decisions average risk R made by a credit analyst is determined by the mathematical expectation of these losses

$$R = \sum_{k=1}^{2}\sum_{m=1}^{2} L_{km} P(V_k, \delta = m) \ , \ k = 1, 2 \ , \ m = 1, 2 \ . \tag{3}$$

where the value $P(V_k, \delta = m)$ denotes the probability of the joint execution of two random events: in accordance with the credit history data, a particular borrower belonged to the class V_k, $k = 1, 2$, and the credit analyst made a decision $\delta = m$ in favor of the m-th class V_m, $m = 1, 2$.

We will evaluate the qualifications of credit analysts as follows:

1. A credit analyst is qualified (Figure 1) if the average risk R of his decisions is less than the a priori risk R_0 of decisions that the bank makes only based on of the probabilities knowledge of trustworthy and untrustworthy clients the appearance, i.e. the strict inequality holds

$$R < R_0 \ . \tag{4}$$

2. A credit analyst A_1 is more qualified than a credit analyst A_2 if the decision-based A_1 average risk R_1 is less than the decision-based A_2 average risk R_2, i.e. the strict inequality holds

$$R_1 < R_2 \ . \tag{5}$$

We will assume that based on the data of previous borrowers credit histories, it is possible to estimate a priori probabilities $P(V_1)$ and $P(V_2) = 1 - P(V_1)$ the appearance of trustworthy and unreliable borrowers.

Based on a retrospective analysis for available credit histories, it is also possible to estimate the values of the conditional probabilities of credit analyst errors

$$P_{12} = P\{\delta = 2 \mid V_1\} , \tag{6}$$

$$P_{21} = P\{\delta = 1 \mid V_2\} \ . \tag{7}$$

We will assume that the losses associated with correct decisions are equal to zero, that is, $L_{11} = L_{22} = 0$. Then, if we take into account that according to the formula for the probabilities product

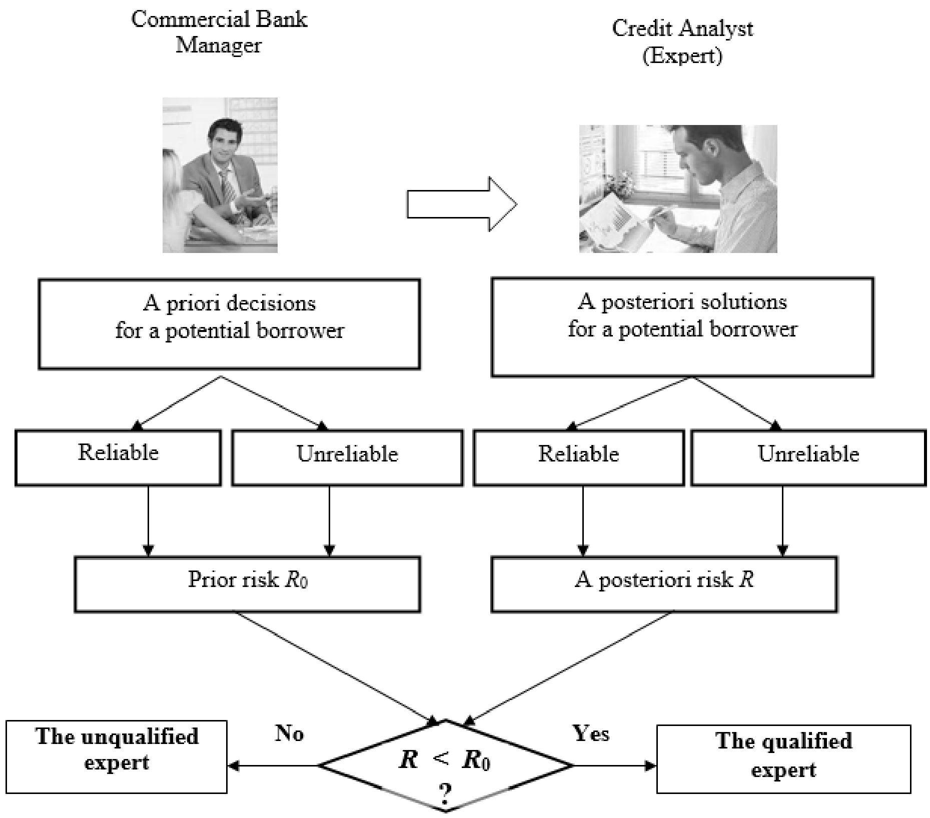

Figure 1. Credit Analyst Qualification Scheme

$$P(V_k, \delta = m) = P(V_k)P(\delta = m \mid V_k) \ .$$

and taking into account the notation (6), (7), the risk of a credit analyst mis-classification (a posterior risk (3)) can be written in an equivalent notation

$$R = L_{12}P(V_1)P_{12} + L_{21}[1 - P(V_1)]P_{21} \ . \qquad (8)$$

Let us now obtain an expression for the a priori risk R_0 appearing on the right side of inequality (4). It is clear that if information about the borrower is not used, then the a priori decisions of the bank are reduced to choosing one of two alternative options: either classify any client as trustworthy (make a decision in favor of V_1), or always make a decision about the unreliability of a potential borrower (make a decision in favor of V_2).

Obviously, in the first case, the a priori risk will be equal to the value

$$R_0^{(1)} = L_{21}[1 - P(V_1)] , \qquad (9)$$

and in the second – the value

$$R_0^{(2)} = L_{12}P(V_1) \ . \qquad (10)$$

Of course, the a priori losses of the bank (a priori risk) are determined by the minimum of the a priori risks of the bank's decisions: to make a decision to issue a loan or not to make such a decision, that is

$$R_0 = \min\{R_0^{(1)}, R_0^{(2)}\} \ .$$

To illustrate the proposed approach, consider a model example.

Model example. An examination of five candidates was conducted to form a group of credit analysts. Existing data from credit histories was used for the exam, which included 70% of good borrowers (repaid the loan without problems) and 30% of bad borrowers (repaid the loan by force). Thus, the a priori probabilities of trustworthy and untrustworthy customers can be estimated by the probabilities $P(V_1) = 0,7$ and $P(V_2) = 0,3$.

Applicants were asked to evaluate their creditworthiness on the basis of the available information about these borrowers. As a result, the conditional probabilities of erroneous decisions for each of the five potential candidates were estimated (Table 1).

Table 1

Probabilistic characteristics estimates based on the testing candidates results

Expert	Conditional probability distribution			
	$P(\delta_1 \mid V_1)$	$P(\delta_1 \mid V_2)$	$P(\delta_2 \mid V_1)$	$P(\delta_2 \mid V_2)$
1	0,95	0,05	0,06	0,94
2	0,942	0,058	0,065	0,935
3	0,941	0,059	0,05	0,95
4	0,987	0,013	0,03	0,97
5	0,948	0,052	0,01	0,99

Let the error loss ratio be $\omega = \dfrac{L_{12}}{L_{21}} = 7$.

Let us determine the risk of making a credit decision without the participation of credit analysts (a priori risk (9), (10)):

$$R_0 = \min\{R_0^{(1)}, R_0^{(2)}\} = \min\{0,3;\ 4,9\} = 0,3 \ .$$

The risk associated with the decisions of the i-th expert is determined by the formula (8). The results are presented in table 2.

Based on the calculated risks of making a credit decision, candidates are identified who, according to formula (4), should be included in the group. Since the risks of the first, fourth and fifth credit analysts are less than the prior risk

$$R^{(1)} < R_0,\ R^{(4)} < R_0,\ R^{(5)} < R_0,$$

then the inclusion of these candidates in the group is expedient.

The risk of the second and third credit analysts is greater than the a priori risk $R^{(2)} > R_0$ $R^{(3)} > R_0$, therefore their inclusion in the group does not make sense.

Credit analysts included in the group are ranked according to (5) based on their qualifications.

Since, according to the values of credit decision risk $R^{(i)}$ calculated in the table 2: $R^{(4)} < R^{(5)} < R^{(1)}$, then the most qualified fourth credit analyst, then the fifth, and then the first.

Table 2

Average risk of decision making by candidates

Expert	Expert decision risk $R^{(i)}$
1	0,263
2	0,3037
3	0,3041
4	0,0727
5	0,2578

Conclusions. Formal conditions that allow assessing the qualifications of a credit analyst in terms of the minimum average risk have been obtained. It is shown that for the practical use of the proposed approach, it is sufficient to estimate the a priori probabilities of trustworthy and unreliable customers in a test sample of credit histories and the conditional probabilities of errors that potential credit analysts make when classifying bank customers with a known credit history. A model example illustrating the proposed approach is presented. Further development of the research of the proposed approach should be directed to the generalization of the obtained results based on the methods of interval analysis [8].

References:

1. Lim M., Sohn S. (2007). Cluster-Based Dynamic Scoring Model. Expert Systems with Applications, vol. 32(2), pp. 427–431.

2. Bidiuk P. I., Danylov V. Ia., Zhyrov O .L. (2017) Otsiniuvannia kredytnykh ryzykiv metodamy intelektualnoho analizu danykh. *Systemni doslidzhennia ta informatsiini tekhnolohii*, no. 1, pp. 33–48. (in Ukrainian)

3. Sustersic M., Mramor D., Zupan J., (2009). Consumer credit scoring models with limited data, *Expert Systems with Applications*, vol. 36(3), pp. 4736–4744.

4. Abdou H., Pointon J. (2011). Credit scoring, statistical techniques and evaluation criteria: a review of the literature. *Intelligent Systems in Accounting, Finance & Management*, vol. 18 (2-3), pp. 59–88.

5. Jasiński A. (2011). Credit Expert – Expert System For Credit Applications Evaluation. *Journal: Ad Alta: Journal of Interdisciplinary Research*, vol. 01, pp. 107–118.

6. Bisbey T. M., Allison M. T., Salas E. (2021). Transforming Teams of Experts into Expert Teams: Eight Principles of Expert Team Performance. *Journal of Expertise*, vol. 4(2), pp. 190–207.

7. Zhukovska O. A., Fainzilberg L. S. (2018). Matematychni modeli kolektyvnykh rishen: monohrafiia. Kyiv: Osvita Ukrainy, 160 p. (in Ukrainian)

8. Zhukovska O. A. (2009). Osnovi interval'nogo analizu: navch. pos. Kyiv: Osvita Ukrainy, 132 p. (in Ukrainian)