Credit rating of natural person by expert knowledge compilation in logic basis of neural networks

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Abstract. The paper discusses the combined use of expert systems and neural network to evaluate the solvency of natural person. Corresponding comprehensive approach to individual credit rating is proposed by compilation of the expert and/or heuristic knowledge about the estimates of the solvency of potential borrowers under uncertainty. Obtained expert estimates of the current solvency of individuals are based on the preliminary expert estimate of influence factors for their ranking and the weights of their relative influence. Adequate translation of the external knowledge relative to weighted summary estimates of natural person solvency in effective internal knowledge is compiled in the logical basis of a multi-layer feedforward neural network.

1. Introduction
The statistical and analytical approaches used today to credit rating of natural person “suffer” from the difficulty of providing the adequate quantitative data relative to the majority of independent variables necessary for the analysis of current and prospective solvency under uncertainty. Therefore, the most balanced approach is considered to be an approach that, combining the best aspects of each of the assessment methods, makes it possible to take into account and interpret not only quantitative, but also qualitative (weakly structured) estimates of the largest number of influence factors the solvency of natural person (NP). In recent years, bank managers have attended to assessing credit risk because of the shortcomings of the existing credit scoring methods and the increasing demand for loans [1].

Existing credit scoring methods basically allow for the binary classification of borrowers, for example, using the neural network method [2], the method of genetic algorithms [3], the decision tree method [4], the vector support method [5], etc. Binary classification is also applied with using the combining methods, for example, combining the previously mentioned method of neural networks and the method of genetic algorithms [6], the method of neural networks and the method of supporting vectors [7].

In [8, 9] we have considered neuro-fuzzy approaches to credit rating of NP, which unlike expert (or scoring) assessment systems are able to compile cause-effect relationships and, thus, reflect the
“internal” view of the task. In addition, for consistent compilation of cause-effect relationships between influence factors and aggregate indexes for comparison of alternatives, or, in other words, to acquired knowledge compilation by translating the external representation of knowledge about weighted total estimations of the alternatives obtained on the base of expert conclusions to effective (adequate) internal representation, in [10] there is suggested an analytical model in the logical basis of the multilayered feedforward neural network. Based on this, this article proposes to evaluate the solvency of NP by the results of the relative influence of solvency indicators (SI) in the logical basis of the neural network. In this case, the problem is formulated as follows.

2. Problem definition
Suppose that to estimate the current solvency of alternative NP the bank uses a set of criteria (or SI), which after some transformations related to the calculation of financial solvency ratios of NP, according to [8] includes: \( x_1 \) is the current and prospective aggregate net income; \( x_2 \) is the volume of deposits; \( x_3 \) is the credit security and its liquidity; \( x_4 \) is Payment-to-Income Ratio (PTI); \( x_5 \) is Obligations-to-Income Ratio (OI); \( x_6 \) is the solvency ratio; \( x_7 \) is the general financial condition; \( x_8 \) is the social stability; \( x_9 \) is the age; \( x_{10} \) is credit history.

Let for a consistent ranking of SI \( x_i \ (i = 1 \div 10) \) the bank involved \( m \) experts from among the most experienced specialists in the field of crediting. At the same time, each \( j \)-th expert is invited to form a rank estimate of the selected SI in the form of \( r_{ij} \) and the corresponding normalized values of the estimates of the SI weights in the form of \( w_{ij} \) relative to following equality: \( \sum_{j=1}^{10} w_{ij} = 1, \ j = 1 \div m \).

This means that the assessment of the relative influence of SI \( x_i \ (i = 1 \div 10) \) on the overall level of NP solvency is carried out by the bank on the base of the consistent implementation of two methods of expertise: comparative qualitative assessment using a ranking method based on the preferences of experts and quantitative assessment – by identifying the weights of SI. Based on these assumptions it is necessary, firstly, to determine the degree of consistency of expert assessments relative to the priority of SI \( x_i \ (i = 1 \div 10) \), secondly, to determine their generalized weights, and, thirdly, to initiate the derivation of the weighted total index, theoretically located in the range of, for example, the segment \([0; 100]\).

The relative weighted influence of SI on the total index NP solvency was considered in [9]. To compile the knowledge about the “external representation” of the crediting process for hypothetical NP with using of a fuzzy inference system in the logical basis of the neural network, we have to repeat some fragments of the [9] with some additions (and/or shortenings). Thus, obtained “external view” of various scenarios of the crediting process under uncertainty specified by presence of weakly structured data relative to SI of NP should be reflected in the form of an analytical model realized in the logical basis of the neural network.

3. SI weight identification by expert analyses
Suppose that for ranking of SI \( x_i \ (i = 1 \div 10) \) in terms of their influence on the overall level of NP solvency, the bank involved 15 experts in the field of crediting. Each of the experts is invited to sequentially position the SI according to the following rule: the most important factor should be indexed with the number “1”, the next less important one – with the number “2”, etc. in descending order of expert preference. As a result of the independent questionnaire survey, the ranking observations of all SI \( x_i \ (i = 1 \div 10) \) are obtained by experts and summarized in the form of table 1.

The degree of consistency of expert opinions is detected by Kendall’s concordance coefficient, which demonstrates the degree of rank correlation of the SI priorities and, according to [11, 12] it is calculated for the general case by formula:

\[
W = \frac{12 \cdot S}{m^2 (n^3 \ - \ n)},
\]  
(1)

2
where \( m \) is the number of experts; \( n \) is the number of SI; \( S \) is the square deviation of expert conclusions from the average value of SI ranking, which is calculated by the following formula [11, 12]:

\[
S = \sum_{i=1}^{m} \left( \sum_{j=1}^{m} r_{ij} - \frac{m(n+1)}{2} \right)^2
\]

where \( r_{ij} \in \{1, 2, \ldots, 10\} \) is the rank of the \( i \)-th SI determined by the \( j \)-th expert \((j=1\div m)\).

In our case, where \( n=10 \) and \( m=15 \), according to (1) the corresponding value of the Kendall’s coefficient of concordance is \( W=0.7993 \), when \( S=14836.5 \) established on the base of (2) and the data from table 1. This value noticeably exceeds the key compliance level threshold of 0.6 [12], which indicates an acceptable agreement of expert ranking scores relative to priority of variable \( x_i \) \((i=1\div10)\). In addition, each expert estimated of the normalized values \( \alpha_{ij} \) of the relative influence of SI, which are also summarized in table 1.

**Table 1. Expert ratings of SI \( x_i \) \((i=1\div10)\).**

| Expert | Estimated SI | \( r_{ij} \) | \( \alpha_{ij} \) | \( x_2 \) | \( x_3 \) | \( x_4 \) | \( x_5 \) | \( x_6 \) | \( x_7 \) | \( x_8 \) | \( x_9 \) | \( x_{10} \) |
|--------|--------------|-------------|----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 01     | 8 0.035 6 0.060 4 0.112 7 0.045 5 0.085 1 0.250 2 0.190 3 0.168 10 0.025 9 0.030 |
| 02     | 7 0.039 9 0.019 4 0.107 8 0.027 5 0.075 1 0.300 3 0.153 2 0.214 10 0.013 6 0.053 |
| 03     | 8 0.033 5 0.083 6 0.061 7 0.045 4 0.112 1 0.275 2 0.204 3 0.151 10 0.014 9 0.022 |
| 04     | 8 0.029 6 0.056 4 0.109 10 0.015 5 0.072 2 0.214 1 0.300 3 0.153 9 0.021 7 0.031 |
| 05     | 8 0.032 6 0.061 5 0.081 7 0.046 4 0.112 1 0.273 3 0.151 2 0.204 10 0.016 9 0.024 |
| 06     | 10 0.022 6 0.065 4 0.112 8 0.038 3 0.147 1 0.255 2 0.194 5 0.086 7 0.052 9 0.029 |
| 07     | 8 0.034 6 0.061 4 0.112 7 0.046 1 0.275 5 0.083 2 0.204 3 0.151 9 0.023 10 0.011 |
| 08     | 6 0.071 8 0.044 4 0.113 9 0.035 5 0.089 1 0.225 2 0.179 3 0.162 10 0.027 7 0.055 |
| 09     | 8 0.038 10 0.022 4 0.113 5 0.086 2 0.194 1 0.255 3 0.148 7 0.050 6 0.065 9 0.029 |
| 10     | 8 0.044 6 0.071 4 0.112 7 0.056 2 0.188 3 0.142 5 0.089 1 0.235 10 0.028 9 0.035 |
| 11     | 7 0.052 8 0.04 4 0.113 6 0.068 5 0.087 1 0.245 2 0.189 3 0.146 10 0.024 9 0.036 |
| 12     | 8 0.046 6 0.072 4 0.112 7 0.058 1 0.215 2 0.183 3 0.149 5 0.097 10 0.031 9 0.037 |
| 13     | 10 0.008 6 0.043 4 0.101 7 0.022 3 0.154 1 0.340 2 0.235 5 0.066 8 0.019 9 0.012 |
| 14     | 8 0.022 4 0.105 6 0.051 7 0.035 5 0.074 2 0.225 1 0.305 3 0.155 10 0.012 9 0.016 |
| 15     | 8 0.034 9 0.025 4 0.112 3 0.151 5 0.083 1 0.265 2 0.204 7 0.046 10 0.018 6 0.062 |
| \( \sum r_{ij} \) | 120 101 105 105 75 24 35 55 139 126 |
| \( \sum \alpha_{ij} \) | 0.539 0.827 1.521 0.773 1.962 3.530 2.894 2.084 0.388 0.482 |

On the base of the obtained results, calculations are carried out for the determination and subsequent identification the weights of \( x_i \) \((i=1\div10)\). For this, group estimates of the normalized values of the relative influence of SI and numerical indicators characterizing the competence of the experts are determined. The average value of \( \alpha_i \) for the \( i \)-th group \((i=1\div10)\) of the normalized estimates of SI is determined according to [9] as following:

\[
\alpha_i(t+1) = \sum_{j=1}^{m} w_j(t) \alpha_{ij},
\]

where \( w_j(t) \) is the weight characterizing the competence degree of the \( j \)-th expert \((j=1\div m)\) at the moment of time \( t \). In this case, the process of finding group estimates of normalized values is iterative, which ends when the condition is satisfied for all \( i=1\div10 \):

\[
\max \{ |\alpha_i(t+1)-\alpha_i(t)| \} \leq \varepsilon.
\]

where \( \varepsilon \) is the allowable error of calculations, for example \( \varepsilon=0.001 \). We assume that at the initial iteration stage \( t=0 \), the experts have the same degrees of competence, which are determined as \( w_j(0)=1/m \). Then for \( i \)-th group the average normalized estimate of the relative influence of SI in the 1st
approximation can be obtained according to (3) as: \( \alpha_i(1) = \sum_{j=1}^{15} w_j(0) \alpha_{ij} = \frac{1}{15} \sum_{j=1}^{15} \alpha_{ij} \). Then the group-averaged estimates of the relative influence of SI in the 1st approximation are the following numbers: \( \alpha_1(1) = 0.036; \ \alpha_2(1) = 0.055; \ \alpha_3(1) = 0.101; \ \alpha_6(1) = 0.052; \ \alpha_8(1) = 0.131; \ \alpha_{10}(1) = 0.235; \ \alpha_1(1) = 0.193; \ \alpha_6(1) = 0.139; \ \alpha_8(1) = 0.026; \ \alpha_{10}(1) = 0.032. \) It is easy to notice that the requirement (4) is not satisfied for the 1st approximation. Therefore, to proceed to the next step it is necessary to calculate the following normalizing factor [9]:

\[
\eta(1) = \sum_{i=1}^{10} \alpha_i(1) \sum_{j=1}^{15} \alpha_{ij} = 2.2198.
\]

Then the experts’ competence indicators at this step are calculated by following equations [9]:

\[
\begin{align*}
w_j(1) &= \frac{1}{\eta(1)} \sum_{i=1}^{10} \alpha_i(1) \cdot \alpha_{ij} \quad (j = 1, 14), \\
w_{15}(1) &= 1 - \sum_{j=1}^{14} w_j(1), \quad \sum_{j=1}^{15} w_j(1) = 1,
\end{align*}
\]

where \( w_{15}(1) \) is the competence degree of the 15-th expert at \( t=1 \). So, according to (5) in the 1st approximation the indicators of expert competence will be: \( w_1(1) = 0.053; \ w_2(1) = 0.056; \ w_3(1) = 0.055; \ w_4(1) = 0.056; \ w_5(1) = 0.054; \ w_6(1) = 0.053; \ w_7(1) = 0.048; \ w_8(1) = 0.051; \ w_{10}(1) = 0.046; \ w_{11}(1) = 0.052; \ w_{12}(1) = 0.048; \ w_{13}(1) = 0.060; \ w_{14}(1) = 0.056; \ w_{15}(1) = 0.261. \) Further, on the base of (3) the group-averaged estimate of the relative influence of SI are calculated as the 2nd approximation:

\( \alpha_1(2) = 0.035; \ \alpha_2(2) = 0.049; \ \alpha_3(2) = 0.103; \ \alpha_6(2) = 0.072; \ \alpha_8(2) = 0.119; \ \alpha_{10}(2) = 0.244; \ \alpha_1(2) = 0.197; \ \alpha_6(2) = 0.024; \ \alpha_{10}(2) = 0.0382. \) As follows from:

\[
\begin{align*}
\max_i \{|\alpha_i(2) - \alpha_i(1)|\} &= \max_i \{0.035 - 0.036, 0.049 - 0.055, 0.103 - 0.101, 0.072 - 0.052, 0.119 - 0.131\} \\
&= 0.037 > \varepsilon,
\end{align*}
\]

condition (4) is not satisfied again. Therefore, starting the next iteration it is necessary to calculate the appropriate normalizing factor as \( \eta(2) = \sum_{i=1}^{10} \alpha_i(2) \sum_{j=1}^{15} \alpha_{ij} = 2.2128. \) In this case, the competence degree of experts \( w_j(2) \) \( (j=1-15) \) are the corresponding numbers:

\[
\begin{align*}
w_1(2) &= 0.053; \ w_2(2) = 0.055; \ w_3(2) = 0.055; \ w_4(2) = 0.055; \ w_5(2) = 0.054; \ w_6(2) = 0.053; \ w_7(2) = 0.047; \ w_8(2) = 0.050; \ w_9(2) = 0.051; \ w_{10}(2) = 0.044; \ w_{11}(2) = 0.052; \ w_{12}(2) = 0.048; \ w_{13}(2) = 0.061; \ w_{14}(2) = 0.056; \ w_{15}(2) = 0.267. \end{align*}
\]

The group-averaged estimates of the relative influence of SI in the 3rd approximation are obtained from the particular case of (3), namely, as: \( \alpha_1(3) = 0.035; \ \alpha_2(3) = 0.049; \ \alpha_3(3) = 0.103; \ \alpha_6(3) = 0.072; \ \alpha_8(3) = 0.119; \ \alpha_{10}(3) = 0.245; \ \alpha_3(3) = 0.197; \ \alpha_6(3) = 0.118; \ \alpha_8(3) = 0.024; \ \alpha_{10}(3) = 0.038. \) At that, according to:

\[
\begin{align*}
\max_i \{|\alpha_i(3) - \alpha_i(2)|\} &= \max_i \{0.035 - 0.035, 0.0486 - 0.0488, 0.103 - 0.103, 0.0723 - 0.0717, 0.1185 - 0.1189\} \\
&= 0.000794 < \varepsilon,
\end{align*}
\]

the accuracy of the group-averaged estimates of the relative influence of SI in the 3rd approximation satisfies condition (4), which means that \( \alpha_1(3), \ \alpha_2(3), ..., \ \alpha_{10}(3) \) are generalized weights of the corresponding SI \( x_i \) \( (i=1-10) \).

4. **Compilation of expert assessments of NP solvency in the logical basis of the neural network**

The method of expert assessments of NP solvency also suggests the discussion on degrees of the influence of the SI \( x_i \) on the values of total solvency indices of NPFL, for example, on following five-point scale: 5 – TOO STRONG; 4 – SIGNIFICANTLY STRONG; 3 – STRONG; 2 – WEAK; 1 – INSIGNIFICANT; 0 – TOO WEAK. Obtained expert assessments are analyzed for consistency (and/or inconsistency) according to the following rule: the maximum allowable difference between two expert opinions on any SI \( x_i \) \( (i=1-10) \) should not exceed 3. This rule allows filtering unacceptable deviations in expert estimates of alternative NP for each concrete \( x_i \) \( (i=1-10) \). Calculation the total index, theoretically ranging from 0 to 100, can be done by following assessment criterion:

\[
\text{(4.1)}
\]
where $c_i$ is the weight of $x_i$ ($i=1\ldots10$), $e_i$ is the consolidated expert assessment of the NP solvency from the point of view of the $i$-th SI influence. In this case, the maximum index means consolidated too strong influence of all SI. 30 scenarios for the formation of credit rating are summarized in table 2.

External knowledge on NP solvency is presented as information model: \( \{(x_{ij}, x_{j2}, \ldots, x_{j10})\rightarrow y_j\}_{j=1,30} \), where $y_j$ is the solvency index of the $j$-th NP calculated by (6). In the case, when quantitative estimates of the relative influence of $x_i$ on the NP solvency level are correct, internal cause-effect relationships can be approximated by a three-layer feedforward neural network (figure 1), which induces the output in the form: \( z_j = \sum_{k=1}^{r} c_k \varphi(w_{kj} x_{ij}) - \theta_k; i = 1,10; j = 1,30 \), where $r$ is the number of nonlinear neurons in the hidden layer (11) selected by the user in the process of simulation; $w_{kj}$ and $c_k$ are the weights of the input and output synaptic relations, respectively; $\theta$ is the threshold of the $k$-th nonlinear neuron from the hidden layer; $\varphi(\cdot)$ is the activation function of nonlinear neuron from the hidden layer.

![Figure 1. Feedforward neural network in notation of MATLAB.](image)

The inputs of the neural network are the signals in the form of 10 numbers from the [0; 5] forming the input vector with 10 components. The one output induces the NP solvency level. To work correctly, according to (6) the network must respond, for example, with the value 3.8809 in the position of the input vector as (0.45; 0.34; 0.29; 0.12; 0.09; 0.09; 0.13; 0.40; 0.11; 0.41). Thus, the produces in the form “input – output” for 30 alternative NP are formed, which is summarized in table 2.

### Table 2. The formation of NP solvency indexes.

| Scenario | Estimated SI | Generalized weights of the SI | The index obtained using the criterion (6) | Index obtained by neural network |
|----------|--------------|------------------------------|------------------------------------------|-------------------------------|
| 1        | 0.035 0.04860 0.10320 0.07230 0.11850 0.24470 0.19730 0.11830 0.02390 0.0384 | 0.0000 | 0.6581 |
| 2        | 0.17 0.26 0.31 0.40 0.56 0.57 0.45 0.23 0.44 0.50 | 8.6131 | 8.6100 |
| 3        | 0.86 0.98 1.00 0.94 0.88 0.91 0.72 0.96 0.85 0.89 | 17.7066 | 16.8182 |
| 4        | 1.42 1.06 1.21 1.54 1.44 1.32 0.32 1.44 1.35 1.48 | 23.1097 | 23.1100 |
| 5        | 1.32 1.44 1.81 1.44 0.64 1.41 1.62 1.67 1.28 1.22 | 28.4884 | 28.4900 |
| 6        | 2.04 2.13 2.14 2.11 1.54 2.17 2.34 1.37 2.14 1.20 | 39.6268 | 39.6300 |
| 7        | 2.49 2.86 1.96 1.02 2.77 2.26 1.54 2.74 3.44 2.17 | 43.5428 | 43.5400 |
| 8        | 2.72 3.14 2.29 4.57 0.16 1.68 3.49 0.43 2.78 4.86 | 47.1124 | 47.1100 |
| 9        | 2.65 1.79 3.92 0.01 2.16 4.94 2.28 1.84 3.48 3.98 | 59.0371 | 59.0400 |
| 10       | 2.88 4.47 0.93 0.25 2.68 1.59 0.08 2.67 3.45 1.87 | 32.4948 | 32.4900 |
| 11       | 4.70 3.77 3.77 0.77 0.16 1.92 1.75 0.81 0.57 2.78 | 36.8434 | 36.8400 |
| 12       | 4.57 3.68 4.73 2.25 3.36 4.68 3.84 3.67 4.79 2.09 | 78.4124 | 78.4100 |
| 13       | 4.46 1.94 0.88 2.12 4.94 3.47 4.96 3.26 3.28 3.42 | 70.0544 | 70.0500 |
| 14       | 4.90 3.04 2.82 1.16 4.30 0.66 1.97 1.95 1.03 1.10 | 41.0315 | 41.0300 |
| 15       | 3.63 4.67 2.88 4.02 4.10 3.16 2.44 2.62 0.69 4.98 | 63.9843 | 63.9800 |
Now suppose that ten individuals appealed to the bank with requests for short-term credits. Since the bank’s resources are limited, it is necessary to choose one NP, who is the best for the package of SI. In this case, all NPs as potential borrowers of credits are alternatives, which we denote as $a_1$, $a_2$, ..., $a_{10}$. Then the calculated values of the performance criterion can be represented in the form of their SI $x_i$ ($i=1$ to $10$), which are summarized in table 3.

### Table 3. Total indexes of alternative NP solvency.

| NP | Estimated SI ($x_i$) | Generalized weights of the SI ($a_i$) | The index obtained using the criterion (6) | Index obtained by neural network |
|----|----------------------|-------------------------------------|-------------------------------------------|---------------------------------|
|    | $x_1$    | $x_2$    | $x_3$    | $x_4$    | $x_5$    | $x_6$    | $x_7$    | $x_8$    | $x_9$    | $x_{10}$ |
| $a_1$ | 2.20 | 0.43 | 1.04 | 3.24 | 1.52 | 3.99 | 1.70 | 0.17 | 4.75 | 1.08 |
| $a_2$ | 2.73 | 3.88 | 2.79 | 4.47 | 3.00 | 4.27 | 2.90 | 2.88 | 2.05 | 2.79 |
| $a_3$ | 1.07 | 2.30 | 3.63 | 4.48 | 1.34 | 2.49 | 3.81 | 2.84 | 3.00 | 1.20 |
| $a_4$ | 3.70 | 2.43 | 1.32 | 2.42 | 2.87 | 0.58 | 3.74 | 3.17 | 1.99 | 4.94 |
| $a_5$ | 1.84 | 4.57 | 1.96 | 4.98 | 3.10 | 2.54 | 4.58 | 3.30 | 0.40 | 4.98 |
| $a_6$ | 4.78 | 3.36 | 4.62 | 3.66 | 2.41 | 4.26 | 2.90 | 4.67 | 3.32 | 0.90 |
| $a_7$ | 0.03 | 1.67 | 3.10 | 2.55 | 1.11 | 1.30 | 4.65 | 1.45 | 4.49 | 1.87 |
| $a_8$ | 4.43 | 1.22 | 4.22 | 3.78 | 0.46 | 1.23 | 2.71 | 1.84 | 1.85 | 4.33 |
| $a_9$ | 1.35 | 1.85 | 3.74 | 3.66 | 0.64 | 4.93 | 4.94 | 1.32 | 1.72 | 2.37 |
| $a_{10}$ | 2.39 | 3.48 | 2.48 | 4.75 | 0.83 | 4.11 | 3.30 | 0.93 | 4.21 | 3.55 |

5. Conclusion

As can be seen from table 3, the solvency indexes of alternative NP obtained using the criterion (6) and the three-layer neural network are in most cases acceptable close to each other, and from the point of view of the order of succession, in both cases the same selection of the best 6th and the worst 1st alternative from among potential borrowers. At the same time, the advantage of the neural network approach is obvious, since in this case, there is no question of involving experts to assess the degree of influence of SI on the level of NP solvency by the five-point assessment scale.

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