A Method for Dynamically Assessing Credit Risk of Internet Financial Service Platform

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Abstract. This paper comprehensively uses the fuzzy cognitive graph method and entropy weight method to dynamically assess the credit risk of Internet financial service platforms. First, a platform credit risk indicator system was constructed. Secondly, the genetic algorithm is used to learn the fuzzy cognitive graph weight matrix. Then, the fuzzy cognitive graph inference mechanism is used to predict the dynamic changes of the credit risk index and the stable state finally achieved. Finally, combined with the index weights calculated by the entropy weight method, the credit risks of the three online lending platforms are dynamically assessed. This paper realizes the dynamic assessment and prediction of Internet financial service platforms, and provides theoretical support for the credit risk of government supervision platforms.

Keywords: P2P network lending, credit risk dynamic assessment, fuzzy cognitive graph.

1. Introduction

Peer to Peer (P2P) network lending is a widely-developed and typical model of Internet finance. It connects lenders and lenders through the Internet and helps the two parties to establish lending relationships and complete a series of transaction procedures through the network platform [1-3].

The continuous development of the platform, its low barriers to entry, and fewer restrictions have led to some problems. Some platforms have issues such as cash withdrawal difficulties, fraud, and mismanagement, which have led to the closure of the platform. As of March 2020, there have been 5,799 platforms that have been closed, run, and difficult to withdraw. The reason is that the poor credit status of the platform itself and the insufficient credit risk management work. Therefore, research on credit risk management of the P2P network lending platform is significant at present, and it is also the subject of this paper.

In practice, the application of the qualitative risk assessment method based on the expert system method is more common [4,5]. They use the methods and techniques in machine learning for credit risk assessment, including data mining technology [6], vector machine technology [7], neural networks [8], etc. The evaluation of credit risk in the above studies is only an evaluation at the past point of time, but credit risk is constantly changing and updating, and it is a dynamic evolution process. The current research has not yet achieved a dynamic assessment of future credit risk. In view of this, considering
that the fuzzy cognitive graph is a commonly used tool for simulating and studying complex dynamic systems, it has a strong ability to express fuzzy reasoning and causality, and a strong ability to explain. The interaction and feedback between the influencing factors can be deduced from the index data to form a corresponding knowledge network. Predict the dynamic change process and the final stable state of the system according to historical laws [9,10]. Therefore, it is effective to apply this tool to credit risk assessment.

2. FCM-based credit risk dynamic assessment

2.1. Fuzzy cognitive map

Fuzzy Cognitive Map is a soft computing method that provides a powerful and flexible framework for knowledge representation, reasoning, and is a convenient tool for dynamic system modeling. The main advantages of FCM are its simple structure, clear expression, smooth operation, and stronger knowledge and reasoning ability [11, 12]. A fuzzy cognitive map is a ternary sequence group:

\[ <X, E, W> \]  

\[ X = [X_1, X_2, \ldots, X_N] \] represents a collection of N conceptual nodes in the FCM diagram. \( E = \{<X_i, X_j>: X_i, X_j \in X\} \) represents a directed arc with a causal association between all conceptual nodes in the FCM diagram. \( W \) represents the link matrix of the link weights between the concept nodes, and \( w_{ij} \) represents the interaction between the concept i and the concept j. If \( w_{ij} > 0 \), it means that \( X_i \) has a positive influence on \( X_j \). If \( w_{ij} < 0 \), then \( X_i \) has a negative influence on \( X_j \). If \( w_{ij} = 0 \), it means that there is no effect between \( X_i \) and \( X_j \).

The mathematical model of FCM reasoning is:

\[ X_j(t+1) = F \left( \sum_{i \neq j} X_i(t)w_{ij} \right) \]

\[ F(x) = \frac{1}{1 + e^{-cx}} \]

where \( X_j(t) \) represents the state value of the conceptual node \( X_j \) at time t; \( X_j(t+1) \) represents the state value of the conceptual node \( X_j \) at time t+1; \( t \) represents the discrete-time, \( t=0, 1, 2, 3, ..., T \); \( F \) is a conversion function that normalizes the value of the concept node to the appropriate range. \( c \) takes a constant greater than 0.

2.2. Extraction of credit risk indicators

Based on the existing research, this paper chooses nine indicators with high citation frequency to study the credit risk of the P2P network lending platform. The details are shown in Table 1.

<table>
<thead>
<tr>
<th>Credit risk indicator</th>
<th>meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1 Volume</td>
<td>Indicates the total amount of the platform that has passed the review within a certain period and passed the review</td>
</tr>
<tr>
<td>X2 The average reference rate of return</td>
<td>The average number of reference yields of all investment targets for a certain period on the online loan platform</td>
</tr>
<tr>
<td>X3 Net inflow of funds</td>
<td>Indicates the amount to be received on the day minus the amount to be received the previous day</td>
</tr>
<tr>
<td>X4 Average loan term</td>
<td>A weighted average indicating the number of times the platform has been traded within a certain period of time.</td>
</tr>
<tr>
<td>Credit risk indicator</td>
<td>meaning</td>
</tr>
<tr>
<td>-----------------------</td>
<td>---------</td>
</tr>
<tr>
<td>X5 Per capita borrowing amount</td>
<td>Representing the platform turnover divided by the number of borrowers</td>
</tr>
<tr>
<td>X6 Amount overdue rate</td>
<td>The ratio of the overdue amount to the loan balance</td>
</tr>
<tr>
<td>X7 Compensation amount</td>
<td>Indicates the total amount repaid by a third party on behalf of the borrower for breach of contract at a certain point in time.</td>
</tr>
<tr>
<td>X8 Loan balance</td>
<td>It indicates the ability of the platform to obtain funds continuously.</td>
</tr>
<tr>
<td>X9 Per capita loan amount</td>
<td>Representing the trading volume of the platform for a certain period divided by the number of investors</td>
</tr>
</tbody>
</table>

2.3. Determination of the influence relationship between hierarchical indicators

The FCM map is constructed based on the interaction between the indicators. Assume that each indicator is related in pairs. The construction results are shown in Figure 1:

![Figure 1(a). Weight matrix of fuzzy cognitive graph.](image1)

![Figure 1(b). FCM Diagram.](image2)

2.4. Calculation of the relationship matrix between indicators

There are many ways to calculate the relationship matrix between indicators, including expert designation and machine learning. The expert designation refers to the expert's assignment of weights between indicators based on experience, which is subjective. Therefore, the research on FCM is now more and more inclined to the machine learning method and learning index weight matrix. Including the Hebbian learning method, particle swarm algorithm, real number coding genetic algorithm. Here, the real-coded genetic algorithm is used to learn the index weights [13, 14].

The relationship weight training pseudo code is as follows.

\[
\text{Initialize parameters such as } p_c, p_m, m, T, \text{ Randomly generate the first generation population pop.}
\]

\[
\text{Do}
\]

\[
\text{Calculate the fitness of each individual in the population pop } F(i)
\]

\[
\text{Initialize empty population newpop}
\]

\[
\text{Do}
\]

\[
\text{Select two individuals from the population pop according to the fitness by the proportional selection algorithm}
\]

\[
\text{If(random } (0,1)< p_c )
\]

\[
\{ \text{Intersection of 2 individuals by crossover probability} \}
\]

\[
\text{If(random } (0,1)< p_m )
\]

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For two individuals to perform mutation operations according to mutation probability. Add 2 new individuals to the population newpop. Until (M children are created) or (any chromosome fitness value exceeds max_fitness, or breeding algebra exceeds m).

2.5. FCM reasoning
The initial state of the index and the weight matrix of the learned fuzzy cognitive graph are input to the inference mechanism. After several iterations, the state of the index tends to be stable and the reasoning ends. Let the initial state of the indicator be \( X(0) = (x_1(0), x_2(0), x_3(0), x_4(0), x_5(0), x_6(0), x_7(0), x_8(0), x_9(0)) \), where \( x_i(0) \in [0,1] \) and the steady state be \( X(t) = (x_1(t), x_2(t), x_3(t), x_4(t), x_5(t), x_6(t), x_7(t), x_8(t), x_9(t)) \).

2.6. Evaluation and grading of credit risk on online lending platform
There are many methods for calculating index weights. In order to overcome the subjectivity of expert opinions, this article uses the entropy weight method to calculate the index weight [15].

2.6.1. Indicator data processing. First, standardize the data. This is shown in Equation (3).

\[
M = \{ m_j \}_{j=1}^{9} (i = 1,2,\cdots,n, j = 1,2,\cdots,9).
\]  

Then, normalize the data and remove the dimensions.

\[
r_{ij} = \frac{m_{ij} - m_{j\text{min}}}{m_{j\text{max}} - m_{j\text{min}}} \quad r_{ij} = \frac{m_{j\text{max}} - m_{ij}}{m_{j\text{max}} - m_{j\text{min}}}
\]  

\( m_{j\text{max}} \) indicates the maximum value of the j-th evaluation index of all the evaluation targets, and \( m_{j\text{min}} \) indicates the minimum value of the j-th evaluation index of all the evaluation targets.

2.6.2. Calculate the weight of each indicator:

\[
q_j = \frac{1 - e^j}{\sum_{j=1}^{9} d_j}, \quad e_j = -k \sum_{i=1}^{n} p_{ij} \ln(p_{ij}), \quad p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{n} r_{ij}}
\]  

Among them, \( k = 1/\ln(n) > 0 \), meets \( e_j \geq 0 \).  

2.7. Calculate the credit risk evaluation value
The linear weighted sum \( R \) of the state value \( x(t) \) and the index weight value \( q \) of the indicator during the iteration is defined as the credit risk evaluation value. If the state value is a steady state value, it is the ultimate evaluation value of credit risk. Its formula is described as follows:

\[
R = \sum_{j=1}^{9} q_j \cdot x(t)
\]  

The greater the credit risk assessment value, the lower the credit risk of the platform. Use 0.6 as the threshold for assessing the level of credit risk. If the platform’s risk assessment value is within the range
of $[0,0.6)$, the platform’s credit risk is high. If it is in the range of $[0.6,1]$, the credit risk of the platform is low.

3. Application case analysis

3.1. Data collection and preprocessing
Select the data of 12 months in 2018 for the three platforms Lu Jinfu, You Wodai, Qing Yidai for modeling and calculation of platform risk assessment. To eliminate dimensions, normalize the data.

3.2. Calculating weight matrix and drawing fuzzy cognitive map
Based on historical data, the genetic algorithm was used to learn the weight matrix of the fuzzy cognitive graphs of the three platforms, and the fuzzy cognitive graphs were drawn. This section uses the Lu Jinfu as an example to draw its weight matrix and fuzzy cognitive map. As the Figure2 shows.

![Figure 2(a). Weight matrix of fuzzy cognitive graph of Lu Jinfu.](image)

![Figure 2(b). FCM Diagram of Lu Jinfu.](image)

3.3. Dynamic changes of indicators after FCM inference
The initial state of each platform and the weight matrix learned by each platform are input into the fuzzy cognitive graph inference mechanism, and the indicator state is inferred and evolved until the system reaches stability, that is, the indicator state value no longer changes. Draw the dynamic change curve of each index during the iteration process, as shown in Figure 5. The initial state values of each platform are shown in Table 2.

<table>
<thead>
<tr>
<th></th>
<th>X1</th>
<th>X2</th>
<th>X3</th>
<th>X4</th>
<th>X5</th>
<th>X6</th>
<th>X7</th>
<th>X8</th>
<th>X9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lu Jinfu</td>
<td>0.2927</td>
<td>0.0000</td>
<td>0.0058</td>
<td>1.0000</td>
<td>1.0000</td>
<td>0.9662</td>
<td>0.1902</td>
<td>0.3152</td>
<td>0.0000</td>
</tr>
<tr>
<td>Ni woda</td>
<td>0.6419</td>
<td>1.0000</td>
<td>0.2733</td>
<td>0.9596</td>
<td>0.4884</td>
<td>0.4731</td>
<td>0.9014</td>
<td>0.4025</td>
<td>0.5517</td>
</tr>
<tr>
<td>Qing Yidai</td>
<td>0.1928</td>
<td>0.4687</td>
<td>0.1340</td>
<td>0.3223</td>
<td>0.0000</td>
<td>0.4911</td>
<td>0.9847</td>
<td>0.5880</td>
<td>0.0688</td>
</tr>
</tbody>
</table>

![Figure 5(a). Indicator dynamic curve of Lu Jinfu.](image)

![Figure 5(b). Indicator dynamic curve of Ni Wodai.](image)
3.4. Comparison of credit risk of different platforms

3.4.1. Weights of indicators. According to the principle of entropy weight method in Section 2.6, the weights of nine indicators are obtained, as shown in Table 3.

<table>
<thead>
<tr>
<th></th>
<th>X1</th>
<th>X2</th>
<th>X3</th>
<th>X4</th>
<th>X5</th>
<th>X6</th>
<th>X7</th>
<th>X8</th>
<th>X9</th>
</tr>
</thead>
<tbody>
<tr>
<td>q</td>
<td>0.0505</td>
<td>0.1862</td>
<td>0.1455</td>
<td>0.0384</td>
<td>0.1836</td>
<td>0.024</td>
<td>0.0644</td>
<td>0.013</td>
<td>0.2944</td>
</tr>
</tbody>
</table>

3.4.2. Limit credit risk evaluation value of each platform. According to formula (6), find the limit credit risk evaluation value of the three platforms and analyze the magnitude of their credit risk. The results are shown in Table 5. The stable state of each indicator is shown in Table 4.

<table>
<thead>
<tr>
<th></th>
<th>X1</th>
<th>X2</th>
<th>X3</th>
<th>X4</th>
<th>X5</th>
<th>X6</th>
<th>X7</th>
<th>X8</th>
<th>X9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lu Jinfu</td>
<td>0.1753</td>
<td>0.8307</td>
<td>0.8146</td>
<td>0.7447</td>
<td>0.7740</td>
<td>0.4520</td>
<td>0.6696</td>
<td>0.6924</td>
<td>0.6753</td>
</tr>
<tr>
<td>Ni Wodai</td>
<td>0.3388</td>
<td>0.8736</td>
<td>0.8478</td>
<td>0.4858</td>
<td>0.6877</td>
<td>0.5902</td>
<td>0.7466</td>
<td>0.5214</td>
<td>0.6553</td>
</tr>
<tr>
<td>Qing Yidai</td>
<td>0.5849</td>
<td>0.8554</td>
<td>0.6473</td>
<td>0.7678</td>
<td>0.5997</td>
<td>0.5911</td>
<td>0.6355</td>
<td>0.3812</td>
<td>0.8358</td>
</tr>
</tbody>
</table>

Table 5. Limit credit risk evaluation value of each platform.

<table>
<thead>
<tr>
<th></th>
<th>Lu Jinfu</th>
<th>Ni Wodai</th>
<th>Qing Yidai</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM credit risk</td>
<td>0.7145</td>
<td>0.7100</td>
<td>0.7287</td>
</tr>
</tbody>
</table>

It can be seen from Table 5 that the risk evaluation values of the three platforms are all greater than 0.6, indicating that the credit risk of the three platforms when they reach a stable state is low. Sorting the credit risk limits of the three platforms, the result is Qing Yidai > Lu Jinfu > Ni Wodai. The credit risk ranking of the three platforms is Qing Yidai < Lu Jinfu < Ni Wodai.

3.4.3. Dynamic curve of credit risk of each platform. According to formula (6), calculate the dynamic change curves of the credit risk evaluation value of each platform, as shown in Figure 6.
On the whole, the credit risk evaluation values of the three platforms is on the rise. This shows that the credit risk of the three platforms is generally decreasing. Among them, the credit risk evaluation values curve of your loan platform rises first and then decreases, that is, its credit risk first decreases and then rises. Lu Jinfu and Qing Yidai have similar credit risk changes. However, the credit risk of Qing Yidai declined slightly faster than Lu Jinfu, and the final credit risk was lower than Lu Jinfu. Therefore, the credit risk of Qing Yidai is low among the three platforms.

4. Summary
To effectively control the credit risk of the online lending platform, this paper aims to evaluate the credit risk of the P2P network lending platform and establishes an FCM-based P2P network lending platform credit risk dynamic assessment model.

First of all, this paper uses the literature measurement method to determine the nine impact indicators of credit risk assessment of online lending platforms. Second, based on historical data, a genetic algorithm is used to learn the fuzzy cognitive graph weight matrix. The reasoning mechanism of fuzzy cognitive graph is used to infer the dynamic change of the state value of each indicator. Then, the entropy weight method is used to calculate the weights of the nine indicators. Calculate and classify the ultimate credit risk assessment for each platform. Finally, draw the dynamic curve of credit risk for each platform. The essence of the FCM method is to learn the historical laws of the credit risk assessment system through historical data, that is, the weight matrix of the FCM. Use the reasoning mechanism of FCM to reason about the future trends and status of the system. In this way, the future risk of the system is dynamically assessed.

Compared with the previous research on the credit risk of the P2P network lending platform, this study evaluates the credit risk of the online lending platform from a quantitative perspective, avoiding the subjectivity of over-reliance on expert opinions, and the assessment is more objective and scientific. In addition, it can dynamically assess the future trend of the credit risk of the platform, and provide theoretical support for the government to monitor the credit risk of the P2P platform.

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