Research on credit risk prediction model based on fuzzy cognitive map

Accepted 21st December, 2022

ABSTRACT

Accurate credit risk prediction is of great significance for commercial banks to prevent non-performing loans effectively. Risk prediction is the key to preventing credit default, reducing the non-performing loan ratio, and enhancing risk identification ability. The commercial bank is a complex system, and the traditional predictive analysis model is challenging to achieve a good prediction accuracy. A credit risk prediction model based on a fuzzy cognitive map is established by learning the weight matrix from historical data. Finally, the model is evaluated by precision, recall rate, accuracy, and other indicators. The results show that this model has a better prediction effect on credit risk, and all the indicators are higher than that of the logistic model and BP neural network model.

Key words: Credit risk, fuzzy cognitive map, non-performing loan ratio.

JEL Classification: M41, C83, L20.

INTRODUCTION

The inundation of bank non-performing loans has become the primary problem troubling the development of the financial industry. Due to various reasons, the four state-owned commercial banks have accumulated many non-performing loans. The non-performing loan ratio of the agricultural bank of China is as high as 30.07%, which directly affects the bank's support to the economy. Due to the economic downturn, the scale of banks’ non-performing loans keeps expanding, and the ratio of non-performing loans increases significantly. Since the end of June 2020, the non-performing loan balance has increased from 2413.5 billion yuan at the end of 2019 to 2,736.4 billion yuan, an increase of 13.38%, and the non-performing loan ratio has increased from 1.86% at the end of 2019 to 1.94% at the end of June 2020 (Table of Main Regulatory Indicators of Commercial Banks in 2020). The non-performing loan amount and non-performing loan ratio of banks have seriously affected the asset safety of banks and increased the operation risk of banks.

There are two main reasons for non-performing loans. First, banks' management level is not high, and risk prevention ability is not strong. Non-performing loans are the inevitable result of extensive bank loan operations. Most of the loans are divided into credit loans and mortgage loans. Although the proportion of guaranteed loans is increasing, there are still problems in the effectiveness and safety of guaranteed loans, and the guarantee degree of loan creditor’s rights is low. There is a severe disconnection between loan power, responsibility, and interest. The quality of bank staff is not high, and some staff with loan power have poor professional quality, resulting in loan loss and failing to prevent corporate debt evasion effectively. Second, a borrower repayment concept is not strong; the solvent is too low, main show is "reversed transmission" bank loans to avoid bank debt. This paper is based on the prediction model of credit risk, mainly for personal credit business, from the basic personal information of nine factors related to the loan as a node. A fuzzy cognitive map combines fuzzy computing and a neural network with intuitive expression and powerful reasoning ability. Viewed from the structure, it is a single-layer neural network, but different from a neural network, it has strong semantics and has strong interpretability for the established model. A fuzzy cognitive map provides a
powerful tool for the analysis and prediction of a complex bank credit system.

RELATED WORK

Because the bank is a complex system affected by many factors, we must adopt a nonlinear method to establish an effective prediction model for credit risk prediction. Hao et al. (2001) used the neural network model to classify the grades of input and output factors. They conducted a comprehensive evaluation of enterprise operating conditions through the index analysis method to analyze the level of risk. This model overcomes the influence of many uncertain factors, conducts more direct and objective evaluation, and provides sufficient scientific basis for bank credit decision-making (Hao et al., 2001). Li and Li (2008) predicted the operating capacity of loan enterprises through the back-propagation network (BP model), thus providing scientific theoretical support for banks' credit decisions and keeping loan risks under control. The above two types of models are neural network models proposed in the early study of credit risk, which can overcome the influence of uncertain factors and objectively predict. Taking all companies listed in Shenzhen and Shanghai before 2005 as samples, Guo (2009) used a logistic model to predict the probability of business failure. They analyzed the model effect without sample proportion. Xiao and Guo (2013) proposed a method to directly extract the transaction behaviors concerned from the transaction data of bank customers, reduce the dimension of the data using principal component analysis, and establish a Logistic regression model to predict the repayment ability of customers' loans. The Logistic and neural network models are early models for credit risk prediction because they can predict effectively and have high prediction accuracy.

Domestic scholars have put forward many nontraditional models to predict credit risk in recent years, including some combination models. Zhan (2014) proposed a forecasting model based on ARMA, which can effectively predict the future risk trend of commercial banks. The non-performing loan ratio is applied to predict the bank's credit risk, and the non-performing loan ratio data within a period is used as a time series for analysis and prediction. Corresponding suggestions are put forward by Zhan (2014). Zhou et al. (2014) used the advantages of the Bayesian network. They could well express the causal relationship between uncertain factors, carry out reasoning decisions and calculate the impact of each indicator on repayment risk. The results proved that this method was influential. Cheng (undated) used a support vector machine (SVM) to establish a credit risk assessment model given the disadvantages of the BP neural network, such as poor reasoning ability and long prediction time. Considering that binary classifiers tend to ignore the relationship between classes, which leads to the problem of low classification accuracy, a multi-classifier construction algorithm based on a support vector regression machine is proposed to transform binary classifiers into three-value classifiers which greatly improves the prediction accuracy. Xiao and Zhu (2018) used a k-means clustering algorithm to build a loan risk model, set up six quantitative objectives and set up a practical system for bank loan risk measurement and management, which effectively improved the security of bank loan risk. At present, the most used portfolio model, researchers can use portfolio model to optimize the model effectively improve the accuracy of credit risk prediction. Liu and Chen (2020) put forward a prediction method of loan risk based on SMOTE and XGBoost, used characteristic engineering for pretreatment and SMOTE algorithm for sampling and balance of positive and negative samples of data, and then built XGBoost classification model. Experimental results show that this method improves the effectiveness of prediction. Wenxue et al. (2017) used the GBDT model to extract portfolio features from data. They then used a Logistic regression model to build a credit risk prediction model with high prediction accuracy.

According to the construction method of the credit risk prediction model proposed in the above paper, this paper adopts a real coding genetic algorithm (RCGA) to construct a credit risk prediction model based on the fuzzy cognitive map. Compared with the method mentioned above, the method proposed in this paper can obtain quantitative causal relationships among various factors through machine learning and has strong knowledge expression and reasoning ability. In addition, the validity of the model is comprehensively considered from such factors as precision, recall rate, and accuracy.

MODEL BUILDING

Due to the confidentiality of customer information, it is difficult for banks to collect credit risk prediction data. This paper uses the data provided by Home Credit Company to make predictions. The Home Credit company is committed to providing services for people without a credit history. The company has 13.353 billion euros of credit in The Chinese market. Based on the data of nine factors as the nodes of the credit risk prediction, including whether there is a room, whether to have a car, Loan-to-income ratio (loan amount/income), Working years income ratio (Working years/income), Income type, education level, marital status, residential status, Working years loan ratio (Working years/loan amount). These nine nodes are related to the customer's financial status, which is a crucial factor affecting the repayment risk.

Fuzzy cognitive map

The Fuzzy Cognitive Map (FCM) combines Fuzzy set theory
and neural network (Fang and Zhang, 2018). Based on the Cognitive Map theory proposed by Axelrod (1976), Kosko (2017) expands the three-valued relationship between concepts into Fuzzy values between [-1,1] in the statement. A fuzzy cognitive map has strong knowledge expression and reasoning ability, which can be qualitative analysis and quantitative expression. From the reasoning mechanism of a fuzzy cognitive map, we can see that it applies to the expression and reasoning between things with a causal relationship and is widely used in decision-making problems (Zhou et al., 2016), prediction problems (Mei et al., 2017), and evaluation problems (Xu and Gong, 2015).

A fuzzy cognitive map is a directed map that connects concepts and their relations in fuzzy feedback dynamical system through arcs, and it emphasizes “structure is meaning.” In a fuzzy cognitive map, knowledge is stored in the relationship between concept nodes, and the process of using knowledge is the function of connection in the system. The connection between nodes describes the logical relationship between them and reflects the interaction between concepts. Because the relationship between concepts is a kind of logical knowledge, and the use process of logical knowledge is an inference process, so the process of mutual influence between concepts can be regarded as a process of inference based on the connection relation and the function of connection is to express the relationship and execute the inference process.

The fuzzy cognitive map can be viewed as a graphical representation of the knowledge of a system, which is composed of concepts and relations between concepts. The concepts can be the system’s events, goals, and trends. The degree of influence between concepts can be expressed by a fuzzy numerical value, which indicates whether the influence between concepts is positive or negative. A fuzzy cognitive map is a single-layer neural network. Concept nodes are similar to neurons and are represented by fuzzy values [-1,1]. Activation is nonlinear. It converts the value after path weighting and activation into a value on [0,1] and inputs it. When the state of a concept node changes, other concept nodes affected by its causality will also change accordingly, thus activating other nodes in the cognitive map. When the new concept node is activated, the feedback will affect the previous node until the system reaches a stable state.

Prediction model construction

A fuzzy cognitive map is expressed by concept nodes, directed arcs between nodes, and weights that indicate the strength of relationships between nodes. It is a directed graph \( <X,E,W> \) composed of concept set \( X \), directed arc \( E \) of connection matrix, and its weight \( W \). There are many factors affecting credit risk, including whether to own a house \((X_1)\), whether to have a car \((X_2)\), loan-to-income ratio \((X_3)\), Working years income ratio \((X_4)\), income type \((X_5)\), education level \((X_6)\), marital status \((X_7)\), residential status \((X_8)\), Working years loan ratio \((X_9)\), these nine factors are highly correlated with repayment risk \((Y)\). So concept set \( X = \{X_1,X_2, X_3,X_4, X_5, X_6, X_7,X_8, X_9, Y\} \). At the same time, we define the initial relationship matrix \( W \) between various influencing factors:

\[
W = \begin{bmatrix}
  w_{1,1} & \cdots & w_{1,10} \\
  \vdots & \ddots & \vdots \\
  w_{10,1} & \cdots & w_{10,10}
\end{bmatrix} # 
\tag{1}
\]

We take these ten indicators as concept nodes, and the directed arcs between them form a fuzzy cognitive map. We constructed a fuzzy cognitive map, as shown in Figure 1, in which the weights of directed arcs are to be determined. Based on the historical data corresponding to the ten indicators, we trained the relational weights between conceptual nodes by using the genetic algorithm based on
real number coding.

**Prediction model construction**

The experiment selects the data provided by Home Credit company, from which 150 samples are randomly selected for predictive analysis. Not all data of selected nodes are numerical values, for example, income type, education level, marital status and residential status are qualitative analysis. In order to unify the data type, we use the following rules to process the data:

- For example, there are four types of income: Working, State servant, Commercial associate and Pensioner. We classify various types according to grade from bad to good, such as Pensioner-1, Commercial associate-2, Working-2 and State servant-3. Education, marital status and residential status were quantified in the same way.
- By looking at the Pearson correlation coefficient of each node, we found that the correlation between working years (year) and the target is the highest, in order to improve the correlation between the target and other lower nodes, we will be compared with the fixed number of year of the work to get the node of the new node (working years income ratio), and the correlation of the target correlation is higher than the most of the nodes. In the same way, we get Loan-to-income ratio and Working years loan ratio.

The unified data are shown in the ten samples in Table 1. Where 0 means no and 1 means yes for a car or house. For repayment risk, 1 represents high repayment risk, and 0 represents low risk. Since the value represents each state value of the fuzzy cognitive map in the interval [0,1], we need to normalize the original data to effectively measure different data of the same node. In this paper, the maximum and minimum method is adopted to standardize data, \(\max(x_i)\) and \(\min(x_i)\) represent the maximum and minimum values in the sample data of the \(i\)th node, \(x_i\) represents the sample data of the \(i\)th node.

\[
y_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}
\]

**Prediction model construction**

There are many construction methods of the fuzzy cognitive map. A traditional fuzzy cognitive map is constructed manually based on expert experience. However, this construction method has substantial limitations and is affected by experts’ knowledge and subjective factors, so the prediction results are challenging to meet expectations. At present, data-driven algorithms are widely used in fuzzy cognitive map construction. Compared with the traditional method based on expert experience, the data-driven algorithm trains and optimizes the weight matrix through a large amount of historical data to obtain a weight matrix with higher prediction accuracy, more robust objectivity and better prediction effect.

Generally, there are two kinds of data-driven algorithms, one is the Hebbian algorithm, and the other is the population-based calculation method. Because the population-based calculation method has powerful searchability, its effect is better than the Hebbian method in most application scenarios. Population-based construction methods include genetic algorithm (GA) (Stach et al., 2010), ant colony algorithm (ACA) (Wu and Shi, 2001), and particle swarm optimization algorithm (PSO) (Zhang et al., 2004). In this study, real coded genetic algorithm (RCGA) is used to train sample data to construct the fuzzy cognitive graph.

A genetic algorithm (GA) is a computational model that simulates the biological evolution process of natural selection and the genetic mechanism of Darwin’s biological evolution. It is a method to search for the optimal solution by simulating the natural evolution process. A genetic
algorithm (GA) will gradually eliminate the individuals with low fitness in the population through selection, crossover, and mutation to retain the individuals with high fitness. After multiple generations of natural selection, the individuals with high fitness will be retained in the population. $err$ in the fitness function represents the mean square error between the actual and predicted values. The formula of fitness and mean square error $err$ is as follows:

$$fitness = \frac{1}{1+err}$$  

$$err = \frac{1}{N \times M} \sum_{i=1}^{M} \sum_{t=1}^{N} (y_i - y_i(t))^2$$

$N$ represents the number of nodes, and $M$ represents the number of samples. The reasoning process of the fuzzy cognitive map is to calculate the concept value in the next iteration based on the current state vector. Its reasoning formula is as follows:

$$\hat{y}_i(t + 1) = F\left(\sum_{j \neq i} w_{j,i} \cdot y_j(t)\right)$$

Where $w_{j,i}$ represents the relational weight between the $j$th concept node and the $i$th concept node, its value range is [-1,1]. We use the weight $w_{j,i}$ obtained by inference to construct the causal relationship between concept nodes and analyze its influence relationship. The weight represents the degree of influence: When $w_{j,i} > 0$, the influence of node $X_j$ on $X_i$ is positively correlated, that is, $X_j$ increases, $X_i$ increases; When $w_{j,i} < 0$, the influence of node $X_j$ on $X_i$ is negatively correlated, that is, $X_j$ increases, $X_i$ decreases; When $w_{j,i} = 0$, there is no influence between the nodes $X_j$ and $X_i$, that is, and there is no directed edge between the two nodes. $\hat{y}_i(t)$ means the state value of the $i$th concept in iteration $t$. $t = 0, 1, 2 \cdots T$ ($T$ is number of iterations); $i = 0, 1, 2 \cdots n$. $\hat{y}_i(t)$ is the value of the $i$th concept calculated from the value after iteration $t$. $F(x)$ is an activation function. After one iteration, the input variable is transformed to a fixed interval [0,1] through the activation function, and the output value is the predicted value. Commonly used activation functions $F(x)$ fall into the following three categories: Two-valued step function, Three-valued step function, and Sigmoid Function (6):

$$F(x) = \frac{1}{1 + e^{-c\alpha}}$$

Where, the two-valued step function maps the $x$ value to the {0,1} set; The three-valued step function maps the $x$ value to the {-1,0,1} set; The sigmoid function maps the $x$ value to the interval [0,1]. Since the state value of each node in the fuzzy cognitive map is required to be between [0,1], the sigmoid function is adopted as the activation function.

For constructing a fuzzy cognitive map, 150 sample data were divided into the training set and test set in the ratio of 7:3. The model is obtained through the training set, and then the test set is brought into the model for predictive analysis. Since the final predicted value is in the range [0,1], we need to set a threshold for the final predicted result to make it a dichotomy problem (0 represents low risk and 1 represents high risk). First, we need to use (2) to normalize the data of the first nine columns in Table 1.

The steps of solving the weight based on the genetic algorithm are as follows:

1) Coding: We selected ten nodes, including 100 weights in total. First, we set the weight of the relationship between nodes and themselves to 0 (they do not influence themselves). The 100 weights are coded in real numbers, $W = \{w_{1,1}, w_{1,2} \cdots w_{10,9}, w_{10,10}\}$. $W$ is the chromosome in the genetic algorithm.

2) Initialize the population: We need to randomly generate a population $M$ of 50 individuals during the construction process.

3) Fitness calculation: The fitness of each chromosome is calculated according to (3.3) and (3.4), and the chromosomes with high fitness are retained. To convert the concept value to [0,1] according to Function (6), we generally set $c$ to 5.

4) Selection: there are many selection methods, such as roulette, random competitive selection, and non-return random selection. In this paper, the roulette selection method is adopted to select the selected chromosomes for the next crossover stage.

5) Crossover: We use a single point of crossover. The crossover points are randomly selected. For chromosomes $W_1$ and $W_2$, we randomly selected one of them as the intersection point and exchanged all elements of the two chromosomes after the intersection point. Before the experiment, we set a crossover probability $pc=0.8$ and randomly generated a decimal between 0 and 1. If the number is greater than the crossover probability, the crossover will be carried out. Otherwise, it will not be carried out.

6) Mutation: the new chromosomes are randomly selected. We set a mutation probability $M_t=0.06$ and randomly generated a decimal from 0 to 1. If the mutation probability is greater than the mutation probability, the mutation will be carried out, and the value of the mutation point will be replaced by the random value on [-1,1].

7) Repeat steps (3) -- (6) to insert new chromosomes into the population until the population limit is reached.

The flow chart of the fuzzy cognitive map prediction model is shown in Figure 2. We obtained the weight matrix as shown in Function (7) through the training of the training set data through the above steps. For the obtained weight matrix, we need to remove the weights with low correlation between nodes to reduce the density of the
weight matrix. We set the threshold to 0.1. If the threshold is too high, the model’s prediction performance deteriorates.

\[
W = \begin{bmatrix}
0 & 0.58 & -0.36 & -0.24 & -0.98 & 0.81 & 0.48 & 0.2 & 0.31 & -0.52 \\
0 & 2 & 0 & 0.22 & 0 & -0.5 & 0.37 & -0.55 & -0.65 & 0.29 \\
-0.84 & 0.7 & 0.36 & 0 & 0.67 & 0 & 0.57 & -0.74 & 0 & 0.83 \\
-0.9 & 0.82 & 0.64 & -0.46 & 0 & 0.48 & 0.27 & 0.58 & -0.25 & 0.17 \\
0.21 & 0.99 & 0.29 & -0.32 & -0.26 & 0 & -0.36 & 0.35 & -0.12 & -0.55 \\
-0.33 & -0.62 & -0.54 & -0.67 & -0.97 & 0 & 0 & -0.81 & -0.98 \\
0.16 & 0.69 & -0.88 & -0.41 & 0.91 & -0.48 & 0.75 & 0 & 0.29 & -0.57 \\
0 & -0.82 & -0.79 & 0.99 & 0.97 & -0.89 & -0.59 & 0.46 & 0 & -0.75 \\
-0.73 & -0.92 & -0.89 & -0.24 & 0.94 & 0.29 & -0.39 & 0.17 & 0.38 & 0
\end{bmatrix}
\]

**Prediction and analysis**

Using the fuzzy cognitive map mentioned above, we predict credit risk according to the prediction model method. We set low-risk customer (0) as a positive sample and high-risk customer (1) as a negative sample. As the final predicted value of the fuzzy cognitive map is a value from 0 to 1, we need to set a threshold value to change it to 0 or 1 for comparison with the real value. We measured the validity of model prediction according to four indexes: Precision, Recall, F1 Score, and Accuracy. According to the prediction results, we can calculate the values of the four indicators through the confusion matrix, as shown in Table 2.

Where TP represents that the true value is a positive sample, and the predicted value is also a positive sample; FN

---

**Table 2:** Confusion matrix.

<table>
<thead>
<tr>
<th>Confusion matrix</th>
<th>Predictive value</th>
<th>Predictive value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Positive sample</td>
<td>Negative sample</td>
</tr>
<tr>
<td>Real value</td>
<td>TP</td>
<td>FN</td>
</tr>
<tr>
<td>Positive sample</td>
<td>FP</td>
<td>TN</td>
</tr>
<tr>
<td>Negative sample</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 2: Prediction flow chart of fuzzy cognitive graph.
represents that the true value is a positive sample and the predicted value is a negative sample; FP means that the true value is a negative sample and the predicted value is a positive sample; TN means that the true value is a negative sample and the predicted value is a negative sample. We extended the four evaluation indexes of model Accuracy, Precision, Recall, F1 Score, and Accuracy according to the confusion matrix. Their formula is as follows:

\[
\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \# \tag{8}
\]

\[
\text{Precision} = \frac{TP}{TP+FP} \# \tag{9}
\]

\[
\text{Precision} = \frac{TP}{TP+FP} \# \tag{10}
\]

\[
\text{Recall} = \frac{TP}{TP+FN} \# \tag{11}
\]

\[
1 \text{Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \# \tag{12}
\]

For these indicators, the accuracy rate represents the proportion of all correctly predicted results in the observed value; Precision means that the predicted value is positive sample results, the model predicts the correct gravity; Recall rate represents the proportion of all outcomes in which the true value of the sample is positive; F1 Score integrates the results generated by accuracy and recall rate, ranging from 0 to 1, where 1 represents good output effect of model and 0 represents harmful output effect.

The first 105 samples were used as the training set to train the weight matrix of the fuzzy cognitive map prediction model, and then the test set was used for prediction. In the confusion matrix, each indicator is calculated, and the prediction results of the logistic model and BP neural network model are compared. The prediction results of each model are shown in Table 3.

Table 3: The confusion matrix of each model.

<table>
<thead>
<tr>
<th></th>
<th>Logistic</th>
<th>BP neural network</th>
<th>FCM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Predictive value</td>
<td>Predictive value</td>
<td>Predictive value</td>
</tr>
<tr>
<td></td>
<td>Positive sample</td>
<td>Negative sample</td>
<td>Positive sample</td>
</tr>
<tr>
<td>Real value</td>
<td>Positive sample</td>
<td>14</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Negative sample</td>
<td>8</td>
<td>16</td>
</tr>
</tbody>
</table>

Table 4: Comparison of experimental results.

<table>
<thead>
<tr>
<th></th>
<th>Logistic (%)</th>
<th>BP neural network (%)</th>
<th>FCM (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precision</td>
<td>66.67</td>
<td>59.38</td>
<td>70.97</td>
</tr>
<tr>
<td>Recall</td>
<td>69.57</td>
<td>82.61</td>
<td>84.62</td>
</tr>
<tr>
<td>F1 Score</td>
<td>68.09</td>
<td>69.09</td>
<td>77.19</td>
</tr>
<tr>
<td>Accuracy</td>
<td>66.60</td>
<td>62.22</td>
<td>71.11</td>
</tr>
</tbody>
</table>

To verify the validity and feasibility of the constructed fuzzy cognitive graph prediction model, we compared the four indicators of the three models (Precision, Recall, F1 Score, and Accuracy) and analyzed the results.

From Table 4, we can see that each credit risk prediction model index based on a fuzzy cognitive graph can reach more than 70%, indicating that the prediction constructed by us is stable and effective. In addition, compared with the Logistic model and BP neural network model, we can find that the model proposed in this paper is higher than the comparison model in all indicators, primarily the index F1 Score, which comprehensively considers the accuracy and recall rate, is significantly higher than 68.09% of the Logistic model and 69.09% of the BP neural network model. In predicting credit risk, we should consider both positive and negative samples, so we mainly measure the prediction ability of the model from the accuracy of prediction. We can see that only the prediction accuracy of the fuzzy cognitive graph model reaches more than 70%. Based on the above consideration, the credit risk prediction model based on the fuzzy cognitive graph is practical and feasible.

Conclusion

According to the above experimental results, the credit risk prediction model based on the fuzzy cognitive map has better prediction than the logistic and BP neural network models. However, this study only considers customers’ basic information as the influencing nodes. If some vital influencing factors such as cash flow can be obtained, model prediction accuracy will significantly increase. The next step should be to consider acquiring data of key influencing factors. In practice, we do not directly choose not to lend money to high-risk customers. If customers can provide collateral such as houses or cars, we can lend money...
appropriately to maximize the bank's interests. The prediction model based on the fuzzy cognitive map proposed in this study is also suitable for the problems of mutual influence between nodes, such as stock prediction and city GDP prediction, and so on, which have practical application value.

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