Research on the Risk Warning of Mobile Payment Based on BP Neural Network

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Abstract: This paper focuses on the risk warning of mobile payment. Based on BP neural network theory, we try to provide a new risk warning method. Firstly, we select the transaction scale of mobile payment as entry point to construct a risk early warning model by using BP neural network. Then, based on the data of development status of China Mobile Payment from 2009 to 2017, we train the model via MATLAB. From the trained model, the transaction scale of 2018 can be predicted, and the prediction error rate is just 5.66%. Finally, by analyzing the weight of input layer of the network, we find the influential economic factors for risk warning, which includes bank card circulation, mobile shopping transaction scale and online shopping user scale.

1. Introduction

According to the latest statistics, the mobile payment industry has developed rapidly. In 2017, China Mobile's payment reached 202.93 trillion yuan. The average growth rate in the past five years was 181%, and the proportion of adult electronic payment was as high as 76.9%. As an emerging product derived from Internet information technology, mobile payment has become an indispensable part of people's lives. At the same time, mobile payment is also facing new challenges and changes. Changes in economic factors and the introduction of national policies will affect the development of this industry and bring new risks.

At present, the research on risk warning of mobile payment is not too much. Wang Liyan introduced the insurance system into the field of mobile payment, and further strengthened the risk warning of mobile payment on the basis of insurance system[1]. Gu Haifeng used AHP and fuzzy analysis to construct a mobile payment risk assessment model [2]. Jiang Xianling focused on the inherent risks of third-party payments and the situational risks of market development [3]. In summary, most scholars study the risks from the perspective of micro, that is, mobile payment itself, but the development of mobile payment is not only related to its own inherent risks, but also affected by the macro factors of economic development.

2. Construction of R-BP Neural Network Model

(1). Initialize the connection weight $W(0)$ and the node threshold $\theta(0)$ of the neural network, and let $GE_{\min} = 0.5$.

(2). Collect training samples $X_p(\mathrm{p}=1,2,\cdots,m)$ and prediction samples $X_q(\mathrm{q}=1,2,\cdots,l)$, the training sample set is used to train the neural network.

(3). Calculating the input and actual outputs of the training and prediction samples at the hidden and output layers .The input and output of the Hidden Layer at the i-th node is

$$HI_{\mathrm{i}} = \sum_j W_{ij} x_j + \theta_i \text{.} \tag{1}$$

$$HO_{\mathrm{i}} = \varphi\left(\sum_j W_{ij} x_j + \theta_i\right) \text{.} \tag{2}$$

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The input and total output of the Output Layer at the K-th node is

$$I_k = \sum_i W_{ki} HO_i + \alpha_k \,. \tag{3}$$

$$O_k = \varphi\left(\sum_i W_{ki} HO_i + \alpha_k\right) \,. \tag{4}$$

Where W_{ij} is the connection weight of the hidden layer; W_{ki} is the connection weight of the output layer; φ represents the excitation function; x_j represents the training data of the input layer; θ_{i} is the node threshold of the hidden layer, and α_{k} is the node threshold of the output layer.

(4). Calculating the prediction error of neural network.

$$GE_{\mathrm{p}} = \frac{1}{2}\sum_k (O_k(x_p) - D_k(x_p))^2 \,. \tag{5}$$

$$GE = \frac{1}{l}\sum_{p=1}^{l} GE_p \,. \tag{6}$$

Where $O_{\mathrm{k}}(x_p)$ is the computed output of the k-th node, $D_k(\mathrm{x}_p)$ is the expected output of the k-th node, and l is the number of training samples. The flow chart of the R-BP neural network model is as follows.

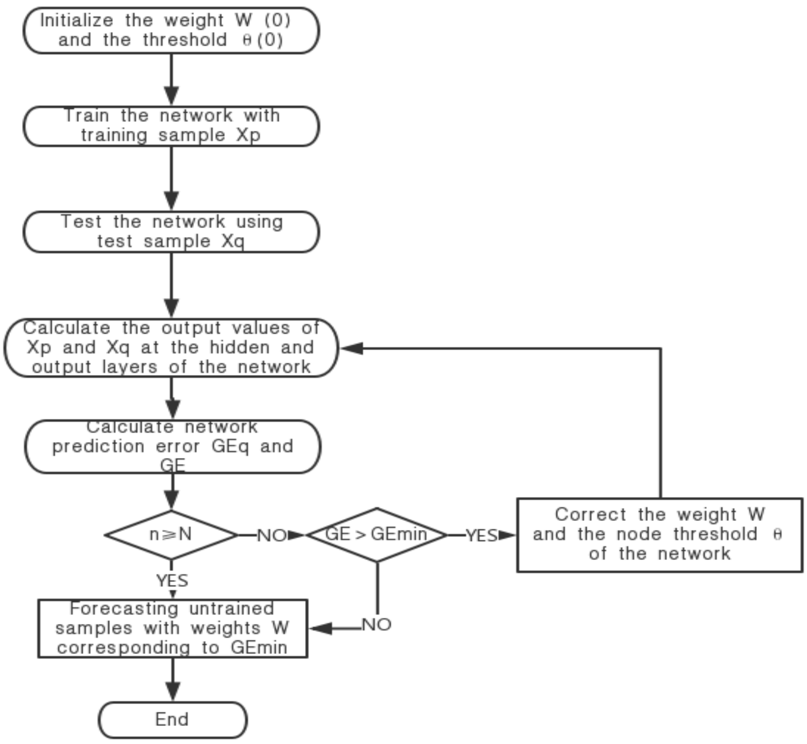

Figure. 1 Neural network flow chart

3. Empirical Research

3.1 Data Acquisition and Preprocessing

We collected relevant data of mobile payment in the past ten years from domestic survey reports, which including economic development factors such as China's Cash Circulation Growth Rate, GDP, Bank Card Issuance, and Online Shopping Users. When studying the risk warning of mobile payment, we start from the transaction scale of the mobile payment industry to study the final impact of other economic factors on the industry. We train the sample multiple times through BP neural network, and get each factor's weight of mobile payment transactions. Finally we find out more significant economic factors, which can provide a reference factor for risk warning of mobile payment.

3.2 Neural Network Estimation of Mobile Payment Transaction Scale

The sample in Table 1 is divided into two parts, there are 9 training samples (numbered 1-9 in Table 1), and one predicted sample (numbered 10 in Table 1). These learning examples are re-expressed by using a multi-layer feedforward neural network.

Where GDP (100 million), China's Cash Circulation Growth Rate (%), China's Total Offline Consumption (100 million yuan), Bank Card Issuance: debit card (100 million), Online Shopping User Scale (100 million), Online Shopping User Growth Rate (%), China's Internet users (100 million), China's Internet penetration rate (%), China Mobile shopping market transaction scale (100 million yuan), etc. expressed by the input nodes of the network. The transaction scale of mobile payment is expressed by the output node of the network. There are 6 hidden layers between the input layer and the output layer of the network. Statistics data are as follows.

Table 1 Mobile payment risk warning data

Num	Time	Y	X1	X2	X3	X4	X5	X6	X7	X8	X9
1	2009	19.74	340507	12.10%	192000	16	1.25	52%	3.71	29.62%	23.51
2	2010	456.73	397980	14.70%	231000	20	1.48	36%	4.73	34.28%	54.8
3	2011	5682.41	471564	15.90%	247000	23	2.03	26%	5.15	38.36%	116.8
4	2012	10300.36	540367.4	9.50%	268000	29	2.84	32%	5.66	42.18%	689.5
5	2013	96400	595244.4	9.30%	282000	33.5	3.25	25%	6.05	45.87%	2740.2
6	2014	225900	643974.1	6.30%	301000	43	3.89	22%	6.21	48.42%	9297.1
7	2015	1082200	685505.8	2.40%	322000	47	4.61	24%	6.57	52.93%	18085.7
8	2016	1575500	744127.3	6.40%	345000	51	5.26	13%	7.12	54.47%	28351.5
9	2017	2029300	820754.2	5.40%	374000	57	5.49	10%	7.49	56.29%	37283.5
10	2018	2773900	900309.2	6.10%	406000	64	6.37	28%	7.88	58.36%	45039.7

The 9 groups of data from 2009 to 2017 were selected as training objects, and the data of 2018 was used for testing. Then we use the simulation function to obtain the network output and verify the reliability of model by checking whether the error between the output value and the experimental measurement meets the requirements.

Using MATLAB7.0 to program simulation, the structure of BP neural network is set to 9-6-1, the transfer function of hidden layer is Tansig, the transfer function of output layer is Pureline, the maximum number of iterations is 50000, and the precision is 0.00001.The results are as follows.

From Fig. 2, we find that when the numbers of training reaches 75 times, the network system error reaches 0.00001, which indicates that the model meets the requirements. From Fig. 3, the maximum prediction error of the BP neural network is 0.0075, which shows that the model training effect is good.

As shown in Table 2, we use the trained BP neural network to predict the transaction size of mobile payment in 2018. The predicted value is 2617000 and the prediction error rate is 5.66%. When using common economic models for prediction, the prediction accuracy of 80% has shown the prediction effect of the model is good, while the prediction accuracy of BP neural network is higher than 80%. Therefore, the research suggests that the model can better predict the scale of mobile payment transactions.

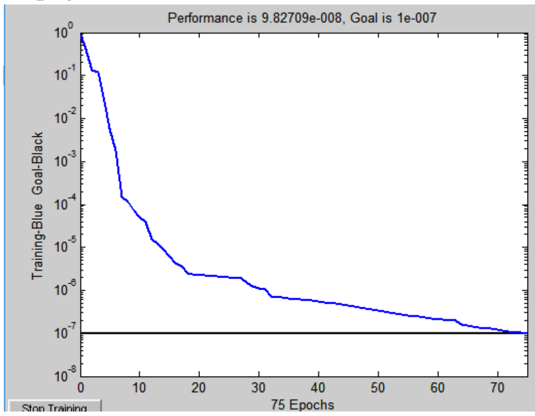

Figure.2 Network training convergence diagram

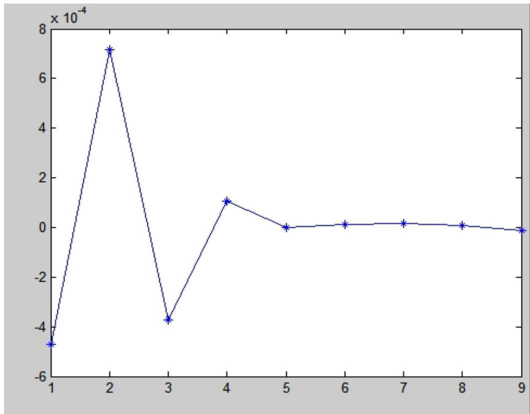

Figure .3 BP network prediction error

Table 2 BP neural network prediction error

Actual value(2018)	Predictive value	Error rate
2773900	2617000	5.66%

In the training process of the sample data, we get the weight matrix $IW_{9\times 9}$ of the network input layer. While the matrix cannot show the extent to which each economic indicator affects the scale of mobile payment transactions. So we further process the weight matrix $IW_{9\times 9}$,Firstly, setting the unit vector $E=\{1,1,1,1,1,1,1,1,1\}$ and $C_{1\times 9}$,where $C=\{c_1,c_2,c_3,c_4,c_5,c_6,c_7,c_8,c_9\}$, ϖ_i is the weight of each economic indicator,as follows

$$C_{1\times 9}=E_{1\times 9}\times IW_{9\times 9}. \tag{7}$$

$$\varpi_i=\frac{c_i}{\sum_{i=1}^{9}c_i}. \tag{8}$$

Table 3 Economic indicators affect weight

Economic Indicators	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
weight	0.0952	0.0947	0.0266	0.1651	0.1561	0.0913	0.1304	0.0806	0.1599

From Table 3, we find that the most significant factors affecting the scale of mobile payment transactions are Bank Card Circulation, Mobile Shopping Transaction Scale and Online Shopping User Scale. In the risk warning of mobile payment, we can not only learn its development trend through the its transaction scale, we can also further explore the possible changes in future through the study of the three significant factors, so as to better implement early warning measures for risks.

4. Conclusion

The data in this article comes from major data consultants, so we can ensure the authenticity of the data. We use BP neural network to train collected risk warning examples of mobile payment, and obtain the result: the model error rate is 0.0017, and the model prediction error rate is 5.66%. The study believes that the training effect of the model is good, and the prediction effect is also up to standard.

The weight of each economic factor on mobile payments can help us determine the value that it can be referenced when it comes to risk warnings. After research, we find that the most significant factors affecting the scale of mobile payment transactions are Bank Card Circulation, Mobile

Shopping Transaction Scale and Online Shopping User Scale. We hope that this paper can provide some help in the research of mobile payment risk warning in the future.

Acknowledgements

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