Analysis of the impact of social network financing based on deep learning and long short-term memory

Abstract: The risk of P2P (peer to peer lending) platform is predicted based on text data on the Internet to avoid the risk of social network financing and improve the security of social network financing. Firstly, the transaction information and review text information of a third-party P2P platform are obtained to be classified for the time series of emotional changes. Secondly, the Granger Causal Relation Test is used to verify the correlation between the time series of emotional changes and trading volume. Finally, a LSTM (Long Short-Term Memory) forecasting model is correspondingly proposed based on investors' emotional changes to predict the trading volume of P2P platforms by emotional changes as a reference for financing social networks to avoid risks. The results show that the value of Pearson correlation coefficient between the trading volume of P2P platforms and negative emotions is -0.2088 with the P value less than 1 %, indicating a correlation between emotional changes and trading volume. The Pearson correlation coefficient between the predicted value and the actual value is 0.7995, while the mean square error is 0.2190 with the fitting degree of 0.6532. This shows that the LSTM forecasting model can well predict the trading volume of P2P platforms with a good performance in the comparison with other forecasting models. In social network financing activities, the LSTM forecasting model can play a good role in risk prediction, as a reference for related research.

Keywords: Deep Learning; Long Short-Term Memory; social network financing; risk forecasting

1. Introduction

In recent years, under the influence of the idea of bucking up China with science and technology, sci-tech innovative enterprises have sprung up, as well as increasingly diversified forms of scientific and technological innovation. Wu et al. (2018) used communication technology and information technology to develop a barrier-free mobile transportation platform to provide more convenient services for the disabled [1]. Science and technology make the life better and better, so the country also provides policy support for sci-tech innovative enterprises. However, these enterprises have invested a lot of funds in technological innovation and R&D (research and development), resulting in low level of internal financial performance of the enterprise [2]. Besides, sci-tech innovative enterprises usually have insufficient risk management consciousness without perfect internal risk management system and anti-risk ability. They cannot even be compared with large enterprises in risk management and control. In short, although venture capital is an important means of raising funds in the short term, many sci-tech innovative enterprises have relatively low ability to control risks and weak ability to resist risks. These enterprises cannot meet the market entry mechanism and market entry standards [3, 4], so it is difficult to raise effective funds in the capital market.

With the development of Internet technology, the emergence of social network [33-36] platform provides a new way of financing for many sci-tech innovative enterprises. As an emerging field that combines the Internet with the traditional financial field, ITFIN (Internet Finance) plays a positive role in large-scale entrepreneurship and innovation, providing many financial conveniences for small and medium-sized enterprises, and making up for the lack of financing for innovative start-ups [5]. However, there are always risks companying with interests. Compared with the existing financial sector, ITFIN has many hidden dangers, such as currency loss, liquidity risk, operation risk, market risk, credit risk [6]. Due to various problems, Internet banks are highly likely to have financial emergencies. P2P (Peer to peer lending) is a representative business model of ITFIN attracting investors' attention while with high possibility of financial emergencies [7, 8]. P2P platform is an online financing platform for P2P financing business. When the payment or repayment ability declines onP2P platforms, the management of the enterprise will cause problems such as corruption, which will lead to financial emergencies [9].

The risk of P2P platform is predicted based on text data on the Internet. Firstly, transaction information and review text information are obtained on a third-party P2P information platform, which are then classified. Secondly, the review text information is classified according to their emotional tendencies, and the time series of emotional trend changes are obtained to achieve the measurement of investors' emotional trends. Then, the correlation between the time series of emotional changes and trading volume is verified by the Granger Causal Relation Test. Accordingly, a P2P trading volume forecasting model is proposed based on investors' emotional changes, hoping to predict and avoid the risk of online lending by grasping the emotional changes.

2. Related Theories and Research Methods

With the continuous improvement of economic level, research on entrepreneurship has become a hot topic at present. Wu et al. (2020) conducted consensus research on social entrepreneurship to analyze the risks and challenges in different stages of entrepreneurship, and the key factors affecting entrepreneurship [10]. Venture capital is the most direct financing channel for sci-tech innovative enterprises, but it cannot fill the huge funding gap of many start-ups. Compared with many other long-established enterprises, sci-tech innovative enterprises are relatively vulnerable. Many sci-tech innovative enterprises need the necessary funds at the initial stage of entrepreneurship, but they face great financing risk due to immature technology development [11, 12]. The emergence of social network platform provides a new way of financing for numerous sci-tech innovative enterprises, along with potential financing risks. Therefore, the risk forecasting of DL (Deep Leaning) technology in social network financing is studied to predict the risk of social network financing of entrepreneurial enterprises [37, 38].

2.1 Related concepts of neural network

Related theories of DL technology as the technical basis of the model are introduced in this section.

RNN (recurrent neural networks) was proposed by M. I. Jordan and Jeffrey Elman et al. Its main function is to solve input problems according to continuous time series. Compared with simple feedforward neural network, RNN has a complete loop structure, which can extract and memorize data. The most representative RNN is Bidirectional RNN and LSTM (Long Short-Term Memory) [13]. The loop structure of RNN is shown in Figure 1.

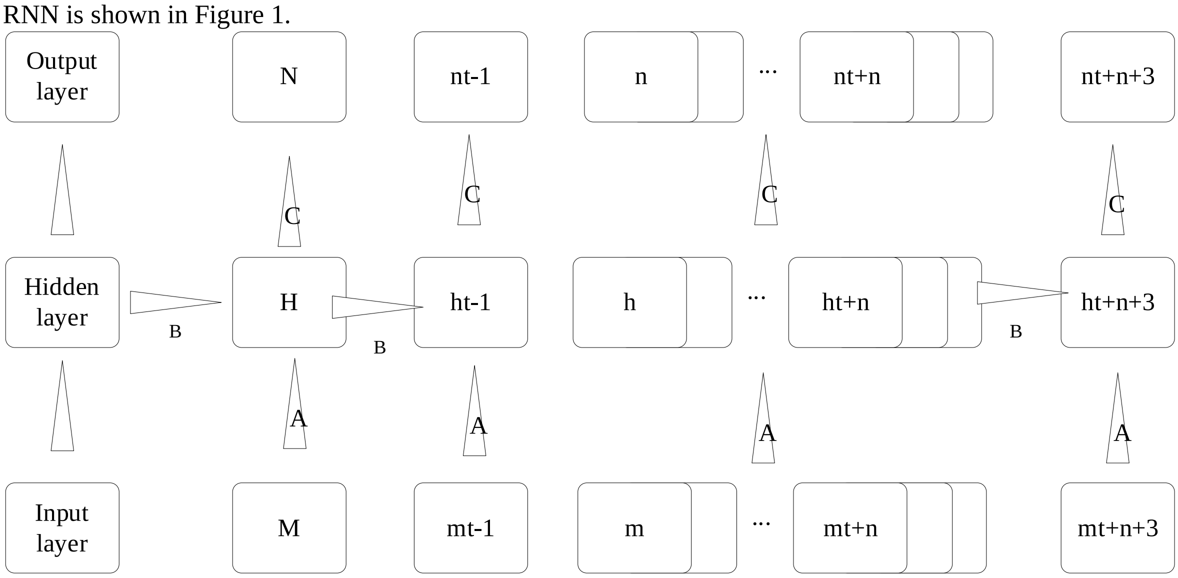


Figure. 1 Loop structure of RNN

In Figure 1, M, H and N represent the input layer, hidden layer, and output layer respectively. Besides, t is the moment of input or output of different nodes. A denotes the weights of the input layer to the hidden layer, while B is the weight of the node at the last input moment, and C shows the weight of the hidden layer to the output layer. According to Figure 1, the forward propagation equations of RNN are presented in Equation (1) and Equation (2).

$$H_t = g(Am_t + Bh_{t-1} + b_h) \tag{1}$$

$$N_t = f(\mathrm{Ch}_t + b_n) \tag{2}$$

The principle of RNN is to find the optimal solution under different weights of A, B and C to minimize the value of the loss function as a whole [14]. The basic propagation principle of RNN is similar to that of feedforward neural network, which uses the time-based BPTT (back propagation through time) algorithm [15]. The BPTT algorithm is an improved version of BP algorithm reversing over time. The communication process is roughly divided into three stages.

1. Calculate the power at each time point during sequence propagation. 2. Calculate the error term of each neuron according to the loss function. 3. Weight update of error back propagation method based on optimization algorithm.

CNN (Convolutional Neural Network) is a multi-layer neural network, which is widely used in the latest field of image recognition and text processing. The original structure of CNN is a new cognitive structure proposed by Kunihiko Fukushima et al. [16]. In 1980, Kunihiko Fukushima et al. proposed the concept of receptive field. In 1989, LeCun et al. used the concept of conventional and BP algorithm in multilayer neural networks, and in 1998 proposed the LeNet-5 model to identify handwritten numbers. This important event made the CNN structure complete [17]. CNN usually consists of three structures, including convolution layer, pooling layer and fully connected layer. The layer neural network outputted after the convolution and pooling operation is used by the template input first for the field of computer image, where the value of pixel can reach millions. Even with direct feedback neural networks, small networks can have more than 100 million parameters [18]. CNN can effectively reduce the number of network parameters by convolution and aggregation operations. In recent studies, CNN has also been widely used in Natural Language Processing.

Convolution operations can reduce parameters by weight sharing and local connections through which other data groups are moved [19, 20]. The weighted convolution kernel (filter) of the input matrix extracts data features from different locations. This process is called convolution, and the extracted features are called feature maps. Multiple convolution kernels can be used on convolution to generate multiple feature maps representing different input features. Figure 2 is a local schematic of the convolution process.

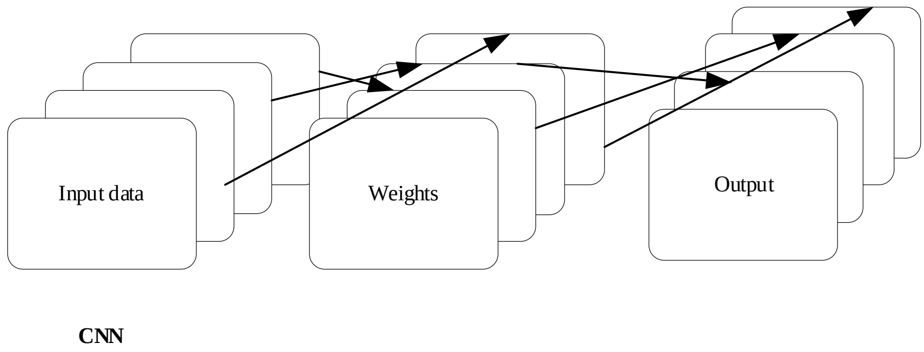


Figure. 2 Schematic of the convolution process

LSTM is short for Long Short-Term Memory, which is the advanced version of RNN. The function of RNN is to process data with logical sequence. In short, it can only process data. Although RNN can save all data generated during data processing, this process will produce a lot of invalid data. Besides, because RNN has a limited number of neurons, many data will be replaced by new data when the memory space is used up, reducing the memory [21]. In other words, RNN can only remember the data recently processed, and the previous data will be forgotten during a long term of data processing. Therefore, the emergence of LSTM is a supplement to this problem. Besides the function of processing logical sequence data, LSTM can output and read the data generated in the processing according to users' needs. It can effectively identify the needed data, and carry out long-term or short-term memory processing according to different data importance, which improves computational efficiency. The structure of the LSTM (unit) is shown in Figure 3.

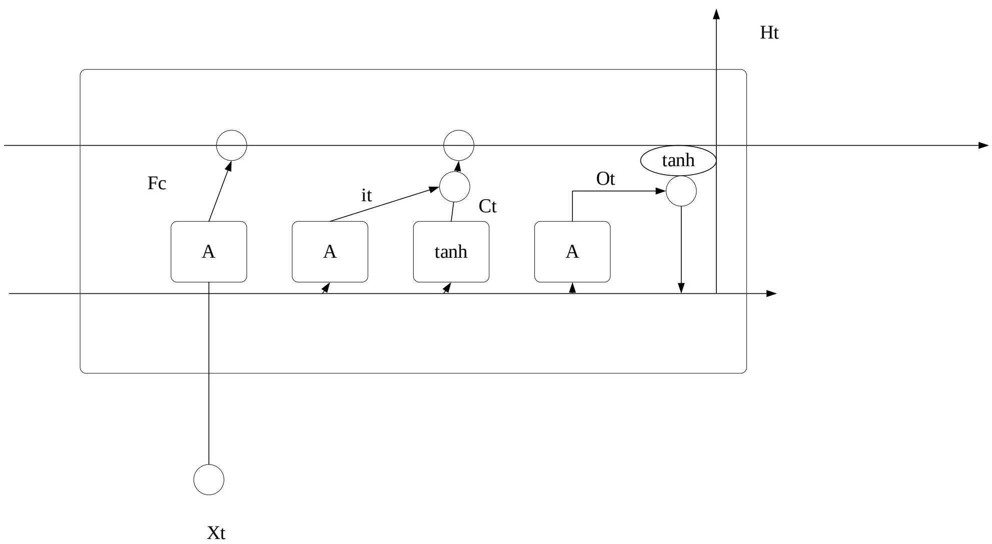


Figure. 3 Unit structure of LSTM

LSTM is composed of many unit structures as shown in Figure 3. This unit structure includes three important parts, namely Fc (forget gate), it and Ct (input gate), and Ot and Ht (output gate). The role of forget gate is to distinguish the data be continuously transmitted downwards from the data for forgetting processing. The role of input gates is to determine what new content is added to the network and is transmitted downward. The role of the output gate is to determine the output information to the next unit structure [22].

2.2 Reasons for financing constraints of sci-tech innovative enterprises

The financing status of sci-tech innovative enterprises is summarized by searching literature and market research. The reasons for the financing constraints of sci-tech innovative enterprises are summarized as follows.

1. Long life cycle. 2. Asymmetric financing information. 3. Weak risk resilience.

Sci-tech innovative enterprises employ sophisticated engineers to create sophisticated products by technological innovation [23]. The whole life cycle of sci-tech enterprises includes four periods, namely germination period, establishment period, development period and maturity period. The different periods of the enterprise's life cycle have different capital demand with different levels of risk and different characteristics of the enterprise. The fund demand of sci-tech enterprises require different financing strategies for different periods of the enterprise's life cycles. However, the homogeneity of financial products of commercial banks is too serious to meet the fund demand of sci-tech enterprises in each period of the life cycle. In the germination period, sci-tech innovative enterprises usually have a small-scale fund demand while with large financing risk. With the development of the enterprise, its fund demand slowly increases and the financing risk gradually decreases. In the establishment period, the enterprise needs small-scale funds mainly used for R&D equipment and market development, which should be based on working capital. However, collateral of the enterprise is relatively weak, mainly for the reason that the enterprise has high financing risk, small asset size, and a little collateral with low value. Therefore, as asset competitors, sci-tech enterprises should not conduct large scale loads in this period [24]. In the development period, the enterprise' technology is continuing to mature and its fund demand is continuing to grow, which depends on the needs of the open market. However, facing greater business risk and technical risk than in the establishment period, the enterprise must take risk prevention measures in the production process to reduce the technical risk of the product and the business risk of the enterprise [25]. Besides, the enterprise should raise funds through capital markets and bank loans. During the maturity period, with the characteristics of stable cash flow, slow financial growth and reduced risk, the enterprise can choose to obtain traditional medium- and long-term loans from commercial banks. The enterprise usually has small financing risk in this period. However, it is also necessary to strengthen industry regulation, and have a positive understanding of industry dynamics, to avoid the company recession. Through the above analysis, in different periods of the life cycle, sci-tech innovative enterprises have different fund demands with completely different risk [26, 27]. Therefore, the financing characteristic of sci-tech enterprises is determined by the various periods of the life cycle.

In terms of financing information, the cost of information collection before loans of sci-tech enterprises at an early stage is higher than that of large state-owned enterprises. Meanwhile, the management and operation mode of sci-tech at an early stage is not as perfect as that of large state-owned enterprises, which cannot truly reflect their business situation. The survey report of China Bank and Insurance Regulatory Commission shows that the insolvency rate of sci-tech enterprises is as high as 22.13% in China, while the loan cost of sci-tech innovative enterprises is 5.1 times that of large state-owned enterprises. The limited development of commercial banks and the imperfect information channels have brought financial constraints to sci-tech innovative enterprises. There is a large information asymmetry between commercial banks and sci-tech innovative enterprises [28].

Sci-tech enterprises commonly have weak anti-risk ability. Numerous sci-tech enterprises have emerged with the policy support of China. As the most direct financing channel for sci-tech enterprises, innovative risk investment cannot fill the huge capital gap of many start-ups. The instable foundation and limited profitability of sci-tech innovative enterprises bring great risks at the starting stage [29]. Therefore, self-financing cannot completely reduce the financing difficulty of sci-tech enterprises. Furthermore, sci-tech innovative enterprises have the characteristics of light assets with no land or other tangible assets as collateral for financing loans, making many commercial banks unwilling to provide loans to them. Without adequate financial support, the risk of project interruption highly increases for sci-tech innovative enterprises.

2.3 Correlation analysis of trading volume forecasting of P2P platforms based on investors' emotional tendencies

With the continuous improvement of science and technology, researchers have been expanding their research fields. Zhou and Wu (2018) pointed out that humble leadership could improve employees' innovative ability. Their study also mentioned the subtle role of emotion [30]. Similarly, emotional change is taken as the research object in the experiment for the risk forecasting of Internet P2P platforms. Besides, the emotional features are vectorized for classification. The experimental data after pre-processing comes from data and messages questioned or exposed by P2P companies on the Internet platform [31]. 82,001 reviews with negative emotions and 129,653 reviews with positive emotions are selected as experimental data for research. The reviews are classified according to emotional tendencies. Since the two types of reviews consist of 100% of the reviews per day, the relationship between emotion and the P2P market can be obtained through the analysis of only one type of reviews. Correspondingly, reviews with negative emotions are selected as the research object to calculate its proportion to total reviews per day. After the normalization calculation and the logistic regression analysis, the Granger Causal Relation Test is used to test the correlation between the negative emotions and trading volume. Equation (3) shows the normalization calculation.

$$N = \frac{X - \overline{X}}{\sigma} \tag{3}$$

In Equation (3), $\overline{X}$ represents the mean of X, and σ is standard deviation.

2.4 Trading volume forecasting model for P2P platforms based on investors' emotion analysis

After analyzing the correlation between investors' emotional tendencies and trading volume, a trading volume forecasting model is proposed based on LSTM. The structure of the model is shown in Figure 4.

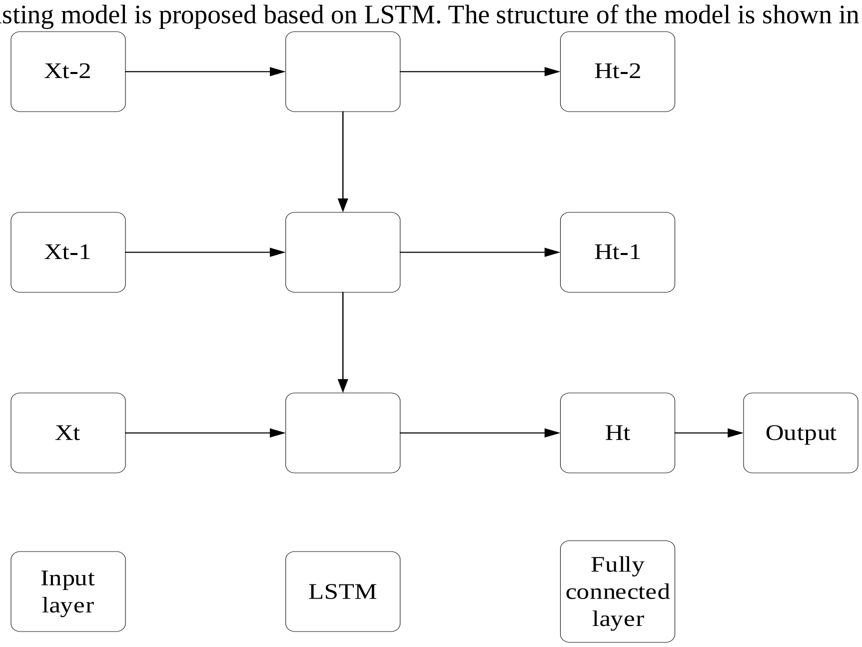


Figure. 4 Trading volume forecasting model based on LSTM

In Figure 4, X represents the input at each moment and H represents the output at each moment. The loss function based on this model is shown in Equations (4) and Equation (5).

$$\mathrm{M} = WsHt + bs \tag{4}$$

$$Loss = \frac{1}{n}\sum_{i=0}^{n}(Mi - mi)^2 \tag{5}$$

In Equations (4), *Ht* represents the input value at the last moment of the output layer of the model, while *Ws* represents the weight of the output layer, and *bs* represents the offset. Besides, *M* represents the output results of the model (same as Equation (5)). In Equation (5), *n* is the size of batch processing.

VAR (Vector Autoregression) model, DNN (Deep Neural Networks), Linear Regression, Random Forest algorithm and SVR (support vector regression) model are selected as the control group to study the effect of the trading volume forecasting model for P2P platforms based on LSTM.

VAR model is a common econometric model proposed by Christopher Sims in 1980. This model uses the multi-equation simultaneous form to regress all the current variables in the model to the lagged variables of all variables, to estimate the dynamic relationship of all endogenous variables. It is an extension of the Autoregression model and has been widely used.

DNN model is the basis of DL, which can be trained by forward propagation and backward propagation. In recent years, it has been used by increasing researchers.

Linear regression is a widely used statistical analysis method that uses regression analysis in mathematical statistics to determine the quantitative relationship between two or more variables. Univariate linear regression analysis includes only one independent variable and one dependent variable, and the relationship between them can use a line as the approximate representation. Multivariate linear regression analysis includes two or more independent variables, and there is a linear relationship between the dependent variable and the independent variable.

Random Forest algorithm is a combinatorial classification algorithm based on ensemble learning. It classifies data through multiple decision trees and can also be used as a regression algorithm. It has many advantages, such as convenience in processing large amounts of data, ability to balance errors, ability to calculate the closeness of each proportion, and fast learning speed [32].

SVR model is an application of SVM (support vector machine) in regression problems. SVM is a kind of generalized linear classifier for binary classification of data by supervised learning. Its decision boundary is the maximum-margin hyperplane for learning samples.

3. Correlation Analysis and experimental results analysis

3.1 Correlation analysis between emotional tendencies and issues on P2P platforms

According to the collected data of the emotional changes on P2P platforms and the issues of P2P platforms, the trend of the proportion of reviews with negative emotion is shown in Figure 5. These data are analyzed by normalization.

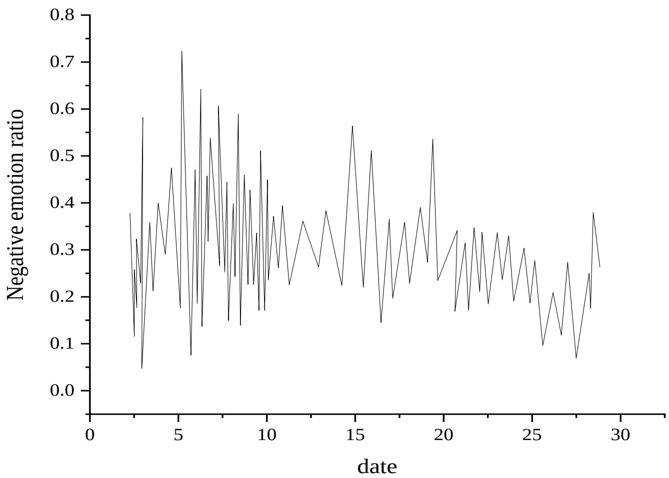


Figure. 5 Proportion of reviews with negative emotions on different dates

From Figure 5, at the same time span, the negative emotions ratio is different by date, but generally fluctuates around 0.5. After calculation, the Pearson correlation coefficient between the trading volume of P2P platforms and negative emotions is - 0.2088, and the P value is less than 1%. This shows that the trading volume of P2P platforms decreases with the increasing proportion of reviews with negative emotions, which is consistent with people’s normal logic.

Based on the data analysis results, the relationship between the negative emotions ratio and the trading issues on P2P platforms is shown in Figure 6.

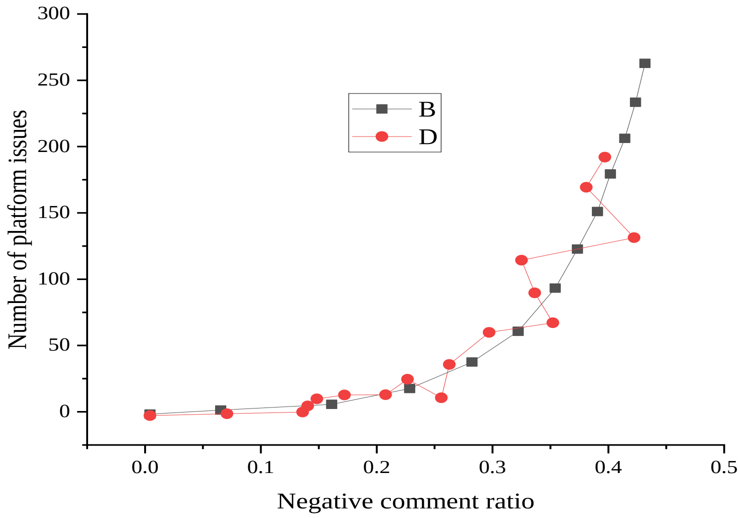


Figure. 6 Relationship between negative emotions ratio and trading volume of P2P platforms (B: logistic curve; D: actual value)

In Figure 6, the negative emotions ratio is positively correlated with the issue quantity of P2P platforms. With the increase in the proportion of negative emotions, the number of issues on P2P trading platforms also increases. After calculation, the Pearson correlation coefficient between the proportion of negative emotional reviews and the number of issues on the P2P trading platform is -0.6523, and the P value is less than 1%. It shows that the proportion of negative emotional reviews has a significant correlation with the number of issues on P2P trading platform. Therefore, it is proved that emotional changes will affect the trading volume of P2P platforms.

The results of stationary test and Granger causality test on time series are shown in Table 1 and Table 2.

Table. 1 Results of unit root test

Option	Actual time series	Negative emotional ratio sequence
T value	-10.8277	-16.8956

According to the stationary test of time series, assuming that there is unit root between them, the possible lower limit of 0.01 is -3.96. According to the actual test results of the unit root, the T value of the actual time series and the negative emotional ratio sequence is less than -3.96. It can be concluded that there is no unit root between the actual time series and the negative emotional ratio sequence. Therefore, the Granger causality test can be carried out.

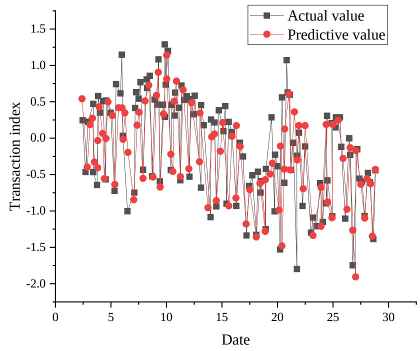
Table. 2 Results of Granger causality test

Date	1	2	3	4	5	6	7
P value	3.8e-09	2.3e-16	1.3e-13	4.3e-14	5.3e-14	9.2e-07	2.1e-08

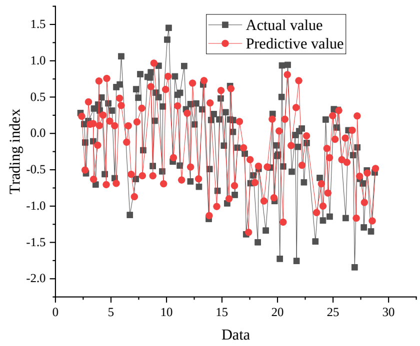
According to the results of the Granger causality test, the maximum value of P is 2.1e-08, far less than 1%. Therefore, there is a statistically causal relationship between the negative emotional proportion sequence and the trading volume of P2P platforms. That is, the trading tendency can be predicted by the emotional changes of both parties.

3.2 Analysis of control experiment results of forecasting effect

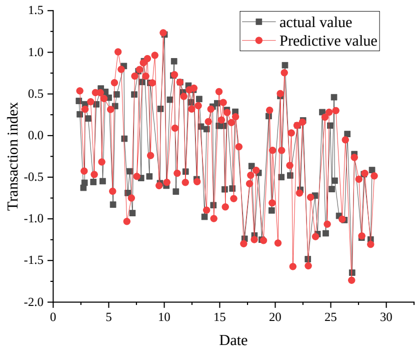
Figure 7 shows the comparison between trading volume forecasting for P2P platforms and the actual trading volume.



(a)



(b)



(c)

Figure. 7 Accuracy rates of forecasting of control groups

In Figure 7, the trading volume of P2P platforms changes periodically. Three groups of different forecast data are selected as the control group to further prove the forecasting effect of emotional changes. Figure 7 (a) shows the comparison between the actual value and the predictive value on the seventh day based on the forecasting results of the previous six days. Figure 7 (b) is the comparison between the actual value and predictive value based on the periodical results and the weekend impact factors. Figure 7 (c) shows the comparison between the actual value and predictive value considering emotional factors. After calculating the data of three groups, it is finally found that the Pearson correlation coefficient of group (a) is 0.6576, the mean square error is 0.4237, and the fitting degree is 0.3756. The Pearson correlation coefficient of group (b) is 0.7325, the mean square error is 0.3178, and the fitting degree is 0.5203. The Pearson correlation coefficient of group (c) is 0.7995, the mean square error is 0.2190, and the fitting degree is 0.6532. From the comparison results of group (a) and group (b), the prediction accuracy has been greatly improved by adding weekend impact factors into the forecast after considering the periodicity of the trading volume of P2P platforms. By comparing the results of group (b) and group (c), after considering the influence of emotional factors, the forecasting accuracy and stability of the model have been improved. In summary, the trading volume forecasting model for P2P platforms based on emotional changes can predict the investment risk of online social platforms.

Figure 8 shows the comparison among the forecasting results of the model based on LSTM, VAR model, DNN model, Linear Regression, Random Forest algorithm, and SVR model to verify the advantages of the forecasting effect of the trading volume forecasting model for P2P platforms based on LSTM.

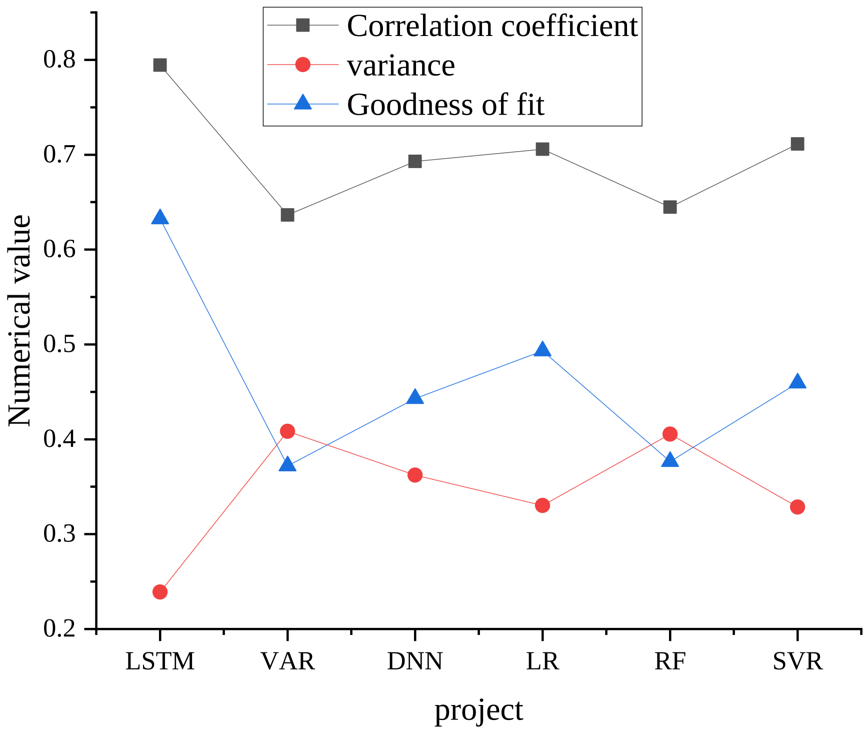


Figure. 8 Comparison of forecasting results

According to Figure 8, the trading volume forecasting model for P2P platforms based on LSTM has advantages compared with other models. The correlation and fitting degree between the forecasting results and the actual value are the highest, indicating that the forecasting value is the closest to the actual value. Besides, it has the highest forecasting accuracy and the lowest variance, indicating that the model has the best forecast stability.

In summary, the trading volume forecasting model for P2P platforms based on DL and LSTM can predict the trading volume of P2P platforms in the short term based on emotional changes with high forecasting accuracy, good stability and good forecasting performance.

4. Conclusion

The risk of P2P platforms is predicted in the experiment based on text data on the Internet. Firstly, transaction information and reviews are obtained from P2P information platforms, and a manual annotation method is established for emotional classification dataset and P2P field. Secondly, the reviews are classified according to their emotional tendencies to obtain the time series of emotional changes to measure investors' emotional tendencies. Then, the Granger causality test is used to verify the correlation between emotional changes and trading volume time series. Based on the above research, a trading volume forecasting model for P2P platforms is proposed based on investors' emotional changes to avoid the risk of online lending. The results show that the trading volume forecasting model for P2P platforms based on DL and LSTM can well predict the short-term trading volume of P2P platforms based on emotional changes with high forecasting accuracy, good stability and good forecasting performance.

However, there is a deficiency in the experiment. The context framework of the model is mainly based on P2P network platforms without involving other social networks. However, the core of the trading volume forecasting model for P2P platforms based on DL and LSTM is to predict the trading volume of social network financing through the study of emotional changes. This method is not only applicable to P2P platforms. How to promote it to more social network financing is the research direction in the future.

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