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ORIGINAL RESEARCH

Identifying Fintech risk through machine learning: analyzing the Q&A text of an online loan investment platform

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Abstract

Financial risks associated with Fintech have been increasing with its significant growth in recent years. Aiming at addressing the problem of identifying risks in online lending investment under a financial technology platform, we develop a Q&A text risk recognition model based on attention mechanism and Bi-directional Long Short-Term Memory. First, the Q&A pairing on the text data set is carried out, and the matching data set is selected for the next analysis. Secondly, the online loan investment platform is assessed by the named entity recognition of the question text. Finally, the risk level of the corresponding investment platform is evaluated based on the answer text. The experimental results show that the proposed model has achieved improved precision, recall, F1-score, and accuracy compared with other models. Our proposed model can be applied to identify the risks from the text posted on online loan investment platforms and can be used to guide investors' investment and improve the management of financial technology platforms.

Keywords Analytics · Attention mechanism · Bi-directional long short-term memory (BiLSTM) · Fintech risk identification · Machine learning

1 Introduction

Innovative technologies have greatly transformed the landscape of business and society. For example, mobile technology is playing an increasingly important role in the evolution of traditional financial services (Franklin 2015; Lonkani et al. 2020). FinTech, a portmanteau word derived from "financial technology", is an emerging economic industry composed of companies that adopt the latest technologies to provide more effective financial

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services than traditional financial services (Lee 2017; Chen et al. 2019; Haddad and Hornuf 2019; Dranev et al. 2019). With the rapid advancement of technology, more and more scholars have begun to pay attention to Fintech (e.g., Dia et al. 2020). At the same time, the inherent risks posed by technology-driven financial innovation such as technical risks, information asymmetry, and even potential systemic risks require regulatory measures to monitor and control (Chao et al. 2018; Yang and Li 2018; Jones and Knaack 2019; Priem 2020).

Over the past decade, the emergence of FinTech companies in the area of consumer and business credit has created many opportunities for lenders and investors. Since 2005, the growth of FinTech investment has been exponential, with its total funding jumping from about \$5.5 billion in 2005 to more than \$10.02 billion in 2017. In the context of alternative financial service operators, a key development is an emergence and rapid growth of peer-to-peer (P2P) Lending platforms (Xu et al. 2015; Ahelegbey et al. 2019). With the growth of the Internet, the P2P loan platform that provides a chance for a better return of investment is becoming many people's top investment choices (Jiang et al. 2018). However, due to the lack of strict supervision, the P2P industry, which has grown very fast in the short term, is also plagued with some problems. A large number of online lending platforms have gone bankrupt or closed for many different reasons. A common reason is that many loans are defaulting, and the borrowers stop paying back. As a result, online lending platforms do not have more money to continue their operations. It is reported that some online lending platforms were even set up to swindle customers, and the owners finally ran away with the money they borrowed from investors. These problematic platforms, especially fraudulent ones, have disrupted the market order of the P2P lending industry and caused severe losses for inexperienced P2P investors. In the financial field, P2P platforms allow direct communication between borrowers and lenders, which is convenient but also worrying. Compared with traditional banks, P2P platforms are less able to process asymmetric information, which leads to investors' inability to distinguish between investment platforms that belong to different credit risk levels (Ahelegbey et al. 2019). Therefore, how to supervise P2P lending platforms and help investors choose which online lending platform for investment are questions that are worthy of study. To answer these questions, a primary task is to conduct risk identification and management.

Financial risk refers to the possibility that the actual return of financial subjects deviates from the expected return due to the change of some factors in the financial market (Marcotte and Grigoriev 2018). Faced with the risks brought by the development of the financial industry, many articles have started to study the problems related to financial risks (e.g., Damel et al. 2016; Morelli 2019). Some scholars are involved in the study of the impact of risk and investment (Wen et al. 2019; Pasricha et al. 2020). Hu et al. (2019a, b) found that there was an asymmetric relationship between the loan interest rate and the borrower's default risk. Specifically, orders with the same interest rate may have different default risks that investors can learn to identify. Similarly, we can learn to identify the risks in the process of online lending. We can use various methods to identify risks. Mishra et al. (2019) studied the factors that affect enterprise risk management and proposed a framework to identify and explain the components of enterprise risk management. The proposed framework allows organizations to deal with increasingly complex risks or identify them over time. Grau-Carles et al. (2019) proposed a new ranking method for different investments according to their stability based on the commonly used ranking methods such as mean, median, *t* test, rank-sum test, and bootstrapping technology, which is very useful for investors. Based on the traditional analysis of network process (ANP) and BW methods, Wang et al. (2019a, b) proposed a risk factor ranking method based on best and worst network (BWN) and ranked 21 risk factors in five risk categories—external environmental, management, financial market, technical, and customer—to identify risks. Some scholars use advanced machine learning and deep learning techniques to study financial risks (Kou et al. 2019; Chen and Tsai 2020).

Previous studies have focused on systemic risks to help management solve the problem of risk control. In contrast, our research focuses on the discovery of risk knowledge from Q&A text in an online loan platform and is expected to make a new contribution to the literature. Based on text emotion analysis, this paper carries out a text risk analysis from the comments of industry participants under their peers' influence to explore the risk information, which adds knowledge to the new investors and further contributes to the investment industry.

Some of the prior studies (e.g., Yuan et al. 2018; Singh et al. 2017; Cheng and Jin 2019; Bag et al. 2019) have examined the impact of text data such as comments on consumers' purchase of products. Emotional analysis of text data (e.g., online reviews) shows that consumers are more inclined to buy products with more positive comments (Salehan and Kim 2016; Xiao and Li 2019). Likewise, in the online investment loan market, investors would like to read both positive and negative comments before they make their investment decisions. According to the positive and negative emotion analysis of the Q&A text, they prefer to choose the investment platform that they believe is relatively safe. However, as the Q&A section data volume is huge, it is hard to make good investment decisions if an investor only sees partial information. Making a decision based on incomplete or partial information is likely to negatively impact the interest of the investors. However, it is unrealistic for investors to read through all of the answers posted on an online lending platform. Furthermore, late responses to questions on an online lending platform also cause information loss since investors cannot obtain complete risk knowledge. To address the research gap, this paper constructs a risk identification model of Q&A text to carry out a simple binary classification of risks and obtain the result of the risk size of an investment platform. Specifically, by using advanced deep learning technology and combining the advantages of BiLSTM and attention mechanism, this paper analyzes a large number of Q&A texts, obtains the risk information contained therein, and thus derives the risk identification results of various investment products. Through these efforts, this paper tries to put forward reasonable suggestions to the three parties in the investment industry: investors, investment platforms, and government regulators to help the sustainable development of the industry. Based on our model, investors can get more comprehensive risk analysis results about an investment platform. According to our findings, investors can choose a low-risk investment platform for investment and lending, which can help them mitigate risks. Meanwhile, our research findings also enable investment platforms to better plan their platform governance, and government agencies to take proper actions to improve regulatory measures for online lending platforms.

The remainder of this paper proceeds as follows. Next section reviews prior studies related to this paper. Section 3 introduces the risk identification model in Q&A text. Section 4 presents the experimental results and analysis. Section 5 concludes the paper with contributions, limitations, and future research directions.

2 Prior literature

2.1 Attention mechanism

Attention Mechanism originated in the study of human visuals (Mnih et al. 2014). In the field of cognitive science, due to the bottleneck of information processing, humans selectively focus on some of the information they see and ignore other visible information, but they can always get the information they want from a limited area. Thus, attentional mechanisms have been proposed to mimic human attentional regions. Attention mechanism is an important idea of deep learning, which can be used to simplify tasks. In the field of computer vision, image recognition tasks can be performed by assigning different weights to different regions of images. Bahdanau et al. (2014) were the first to introduce the attention mechanism into the neural machine translation system based on the encoder-decoder framework to solve the problem of input–output misalignment. Attention mechanism was also applied to the field of natural language processing (NLP) to process text data (Huang et al. 2018; Peng et al. 2019; Zhao et al. 2019), identify text features, and learn text semantics. The essence of attention mechanism is to assign different weights to each feature in a group of them to obtain the feature that has a great influence on the result. Based on the analysis of the text data, our research applies the theory of attention mechanism to assign a different weight to each word in a sentence and focus on the important words to obtain strong semantic expression.

2.2 Bi-directional long short-term memory

In recent years, deep learning technology has been developing vigorously. The artificial neural network has been applied in more and more fields, especially in the field of Natural Language Processing (NLP) (e.g., Kumar et al. 2020). The relevant technologies and their characteristics are shown in Table 1.

Convolution Neural Network (CNN) (Zhou et al. 2017) usually contains a convolution layer, drop sampling layer, full connection layer, and output layer; the convolution layer and drop sampling layer can be multiple. The convolution layer is used for feature extraction. It is characterized by sparse connections and weight sharing. The sampling layer will select a small area of input features, which can quickly reduce the space size of data and ensure that CNN has a certain anti-noise capability. In NLP tasks, CNN can carry out the convolution extraction of text features on the word vector matrix of text data transformation to learn text semantics.

Recurrent Neural Network (RNN) (Yang et al. 2018) is a serial data model, it can learn the semantic expression of sequence context in the process of acquiring information, and calculate the output of the current moment by acquiring the output of the previous moment and the current input. RNN can learn current semantic expressions more accurately by considering the previous information. However, when RNN is expanded over time, it can be

Table 1 Advanced natural language processing technologies and their characteristics

Technology	Characteristic
Convolution neural network (CNN)	It can carry out convolution extraction of text features on the word vector matrix of text data transformation
Recurrent neural network (RNN)	It can learn the semantic expression of sequence context in the process of acquiring information, but there is a serious gradient dissipation phenomenon
Long short-term memory (LSTM)	It can alleviate the gradient dissipation phenomenon and learn the impact of the text forward information on the current output
Bi-directional long short-term memory (BiLSTM)	It can fully consider the influence of context information on current output

regarded as a very deep feed-forward neural network, and there is a serious gradient dissipation phenomenon, which leads to its inability to learn the long-range dependence in data. When the text sequence is long, it cannot accurately learn the text semantics. For example, when an expression that is contrary to the current text is very far forward, it learns the exact opposite semantics and completely departs from the information we want.

To alleviate the gradient dissipation phenomenon in RNN, Long Short-Term Memory (LSTM) (Yang et al. 2018) adds three control units of input gate, output gate, and forget gate on its basis. When information enters the model, the three control units in LSTM will judge the information, and the information that conforms to the rules will be left behind, and the information that does not conform to the rules will be forgotten, so that some important information can be retained forever. Therefore, the problem of long sequence dependence in a neural network can be solved and the semantic expression of long text can be effectively studied. However, for some text content, the subsequent information also has a great impact on the current output, while LSTM only considers the impact of the text forward information on the current output, without considering the impact of the text backward information on the current output. Bi-directional Long Short-Term memory (BiLSTM) (Xu et al. 2019a, b) is composed of two positive and negative LSTM, which can fully consider the influence of context information on current output, learn more accurate semantic expression of the text, and have a more comprehensive semantic understanding of the text.

2.3 Related studies on identification of financial risks

The development of science and technology has facilitated the progress of the financial industry, but financial risks are still inevitable. Many scholars have done a lot of research on the identification of financial risks. A relevant literature review is shown in Table 2.

To gauge the systemic risk of banks, financial services, and insurance firms, the Delta Conditional Value-at-Risk (increment CoVaR) methodology is applied by Zeb and Rashid (2019). They used the panel regression approach to examine how firm-specific variables determine the level of systemic risk in different financial institutions of BRICS countries. Tsionas (2016) estimated banking risks using data for Eurozone countries based on parameters such as risk aversion, prudence or downside risk aversion, and generalized risk resulting from a factor model of loan prices. Considering that banking risks are endogenous, Delis et al. (2017) proposed a model of frontier efficiency to measure the risks using panel data for U.S. banks with Bayesian techniques. Slusarczyk and Grondys (2019) analyzed the impact of selected parametric characteristics of the SME sector on the intensity of financial risk they take. Brunner-Kirchmair and Wiener (2019) discussed the existing problems of financial risk identification and assessment methods. They contributed to the existing literature by proposing collaborative financial risk assessment (CFRA) as a solution to those problems and adding a new perspective to financial risk governance. These studies show that risk identification is important. In this article, we use deep learning methods to identify the possibility of risks and provide some suggestions for investors. Wang et al. (2020) proposed modified CreditMetrics model and Monte Carlo simulation to investigate banks' risk preference. Financial system risk is an important problem in economics and financial system. In order to detect and respond to systemic risks through the growing amount of data produced in financial markets and systems, many researchers are increasingly using machine learning methods (Kou et al. 2019). In combination with machine learning techniques, including big data analysis, network analysis, and sentiment analysis,

Table 2 Relevant literature review

Author (year)	Title	Risk type	Method
Tsionas (2016)	Parameters measuring bank risk and their estimation	Banking risk	Explicit model of expected utility maximization
Delis et al. (2017)	Endogenous bank risk and efficiency	Banking risk	Bayesian techniques
Zeb and Rashid (2019)	Systemic risk in financial institutions of BRICS: measurement and identification of firm-specific determinants	The systemic risk of banks, financial services, and insurance firms	Panel regression approach
Brunner-Kirchmair and Wiener (2019)	Knowledge is power-conceptualizing collaborative financial risk assessment	Financial risk	Collaborative financial risk assessment (CFRA)
Wang et al. (2020)	A method to evaluate credit risk for banks under PPP project finance	Banking risk	Modified CreditMetrics model and Monte Carlo simulation
Zhong and Zhou (2020)	Risk analysis method of bank microfinance based on multiple genetic artificial neural networks	Microfinance risk	Multi-gene artificial neural network
Liu and Huang (2020)	Supply chain finance credit risk assessment using support vector machine-based ensemble improved with noise elimination	Supply chain financial risk	Ensemble support vector machine model

they reviewed the existing research and methods of risk assessment and measurement in financial system. Wei et al. (2019) innovatively applied the text mining approach to comprehensively identify energy corporate risk factors from textual risk disclosures reported in financial statements. Zhong and Zhou (2020) studied the risk of microfinance based on multi-gene artificial neural network and provided theoretical and practical applications for the risk management of microfinance enterprises. They proved the validity and applicability of the neural network in the field of farmers' microcredit risk assessment. Liu and Huang (2020) proposed an ensemble support vector machine model to solve the risk assessment of supply chain finance, combined with reducing noises method. The results indicated that the method could improve the accuracy of credit evaluation. Mosteanu and Faccia (2020) presented how artificial intelligence may combine financial information with tech capabilities, accelerate digital transformation of finance and accounting, and create a safe business and economic environment to reduce human errors.

Inspired by the existing literature, this paper mines and analyzes Q&A text data from the net credit platform using advanced text processing, machine learning, and artificial intelligence technology. Our research attempts to find out some interesting and meaningful information, to make useful recommendations for consumers and managers in online loan transactions.

3 Model

Aiming at identifying financial risks from the Q&A texts posted on an online lending platform website (P2P EYE), this paper proposes a risk identification model based on attention mechanism. The overall structure of the model is shown in Fig. 1.

First, the text data set was matched with Q&A to remove invalid text that failed Q&A matching. Then, the name of the online loan investment product is obtained by the named entity recognition of the question text and the risk level of the answer text is analyzed. Finally, we output the name of the online loan investment product and its risk identification result. The technical details are provided below.

3.1 Q&A pairing based on attention mechanism

In the Q&A text, many answers have nothing to do with the actual problems, or they may digress from the topic, which usually appears in the relatively long answers (Fan et al. 2019). Most of the Q&A responses we have collected are long texts, and inevitably some of them contain irrelevant answers. There's no point in studying such texts. Therefore, we first need to match the text with the question and answer, and then delete the text data that failed to match, analyze, and process the successfully matched Q&A text data set. In this paper, inspired by Wang et al. (2019a, b), a Q&A pairing model based on attention mechanism is constructed, which is shown in Fig. 2.

The word coding layer has four inputs: the sentence before the current answer, the current answer, the sentence after the current answer, and the question. Word2Vec is used to pre-train the word vectors and to represent the four inputs with the word vectors. The semantic learning layer uses four BiLSTM to simultaneously encode the question and answer text into contextual word vectors, as shown in Eqs. (1)–(4). BiLSTM can be used to better learn the upper and lower semantic expression of the text.

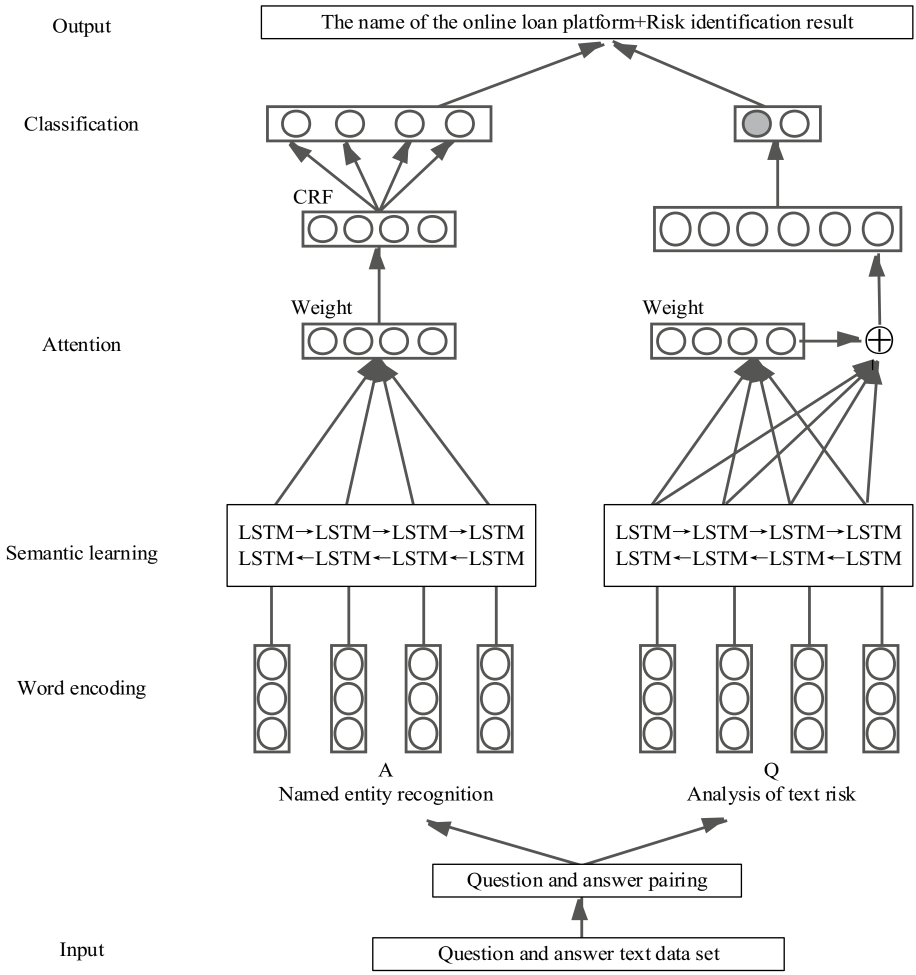

Fig. 1 Financial risk identification model based on attention mechanism

$$H_f = \overrightarrow{LSTM}(A_f) \oplus \overleftarrow{LSTM}(A_f) \tag{1}$$

$$H_a = \overrightarrow{LSTM}(A_a) \oplus \overleftarrow{LSTM}(A_a) \tag{2}$$

$$H_b = \overrightarrow{LSTM}(A_b) \oplus \overleftarrow{LSTM}(A_b) \tag{3}$$

$$H_Q = \overrightarrow{LSTM}(Q) \oplus \overleftarrow{LSTM}(Q) \tag{4}$$

where H_f, H_a, H_b and Q are the word vector expressions of the sentence before the current answer, the current answer, the sentence after the current answer, and the question.

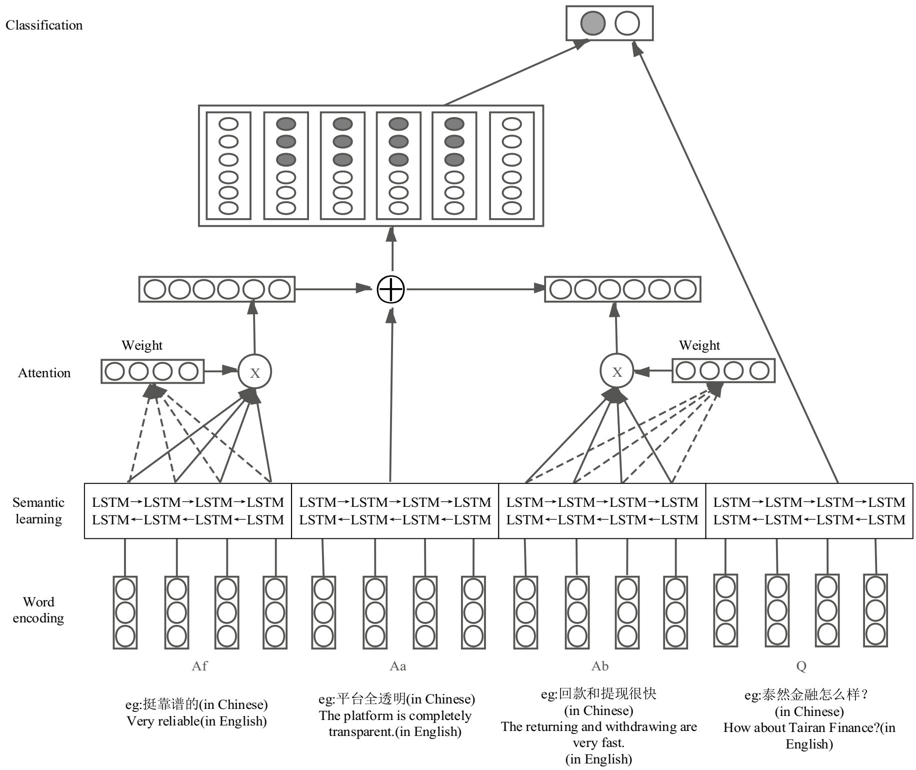

Fig. 2 Q&A pairing model based on attention mechanism

The attention mechanism can focus on keywords in the attention layer. It is employed to assign a weight to the word vector to obtain the most informative representation of the current sentence. They are written as:

$$a_f = soft\ \max(\tanh(W_f H_f + b_f)), \tag{5}$$

$$a_b = soft\ \max(\tanh(W_b H_b + b_b)), \tag{6}$$

where W_f and W_b are the weight, b_f and b_b is the bias.

Then we calculate the sentence vectors of before and after the current answer; they are written as:

$$v_f = a_f H_f, \quad \text{and} \tag{7}$$

$$v_b = a_b H_b. \tag{8}$$

We link the current answer and the sentences of before and after it to get a context-sensitive representation, which is written as:

$$H_A = v_f \oplus H_a \oplus v_b. \tag{9}$$

The classification layer calculates the similarity between two vectors of question and answer by cosine function to get the Q&A vector v_{AQ}. We pass it into the softmax classifier for sorting, which is written as:

$$O = Wv_{AQ} + b, \tag{10}$$

where W and b are the weight and bias, and O is the output.

Finally, the one with the highest probability is the classification result. We select the Q&A text matching successfully for the next processing.

3.2 Named entity recognition based on attention mechanism

Named Entity Recognition (NER) is often used to identify names and places in the text and other entities with a specific meaning. Hu et al. (2019a, b) used NER to identify the place names with vernacular nature. In this paper, NER is used to identify the investment platform in the question text. There are three traditional NER methods (Liu and Wang 2018). The first method is a rule-based approach, the second is based on statistics, including HMM, conditional random field (CRF) model, and Viterbi algorithm, and the third is neural networks. Because of the context-dependence of text, LSTM, a sequence model that can store context information can achieve good results. CRF is a global normalization model that combines the characteristics of the maximum entropy model and the hidden Markov model to find the best output sequence considering the dependence between continuous labels. Na et al. (2019) used the combination of LSTM and CRF to conduct NER better than traditional CRF. Xu et al. (2019a, b) applied the attention mechanism in BiLSTM to conduct NER. In this paper, the advantages of attention mechanism and BiLSTM are combined with CRF to enhance the effect of NER.

First, the context information of the answer is extracted through BiLSTM, and then the keywords in the answer are weighted by the attention mechanism. CRF score is written as:

$$S(v) = \sum_{i=1}^{n} P_{t,v_i} + \sum_{i=0}^{n} A_{v_i,v_{i+1}}, \tag{11}$$

where $A_{v_i,v_{i+1}}$ is the transfer characteristic matrix used to store the probability of transferring between all tags, n is the number of tags, and i represents the current tag.

The classification layer uses the CRF score to classify and the final subject recognition result is shown in Table 3.

3.3 Text risk analysis based on attention mechanism

In this part, textual risk analysis is carried out for the answers of the online loan Q&A text that have been successfully matched. The positive and negative results obtained by emotional analysis have a great impact on investors. Investors tend to avoid investment platforms with more negative answers and prefer to choose investment platforms with more positive answers. Based on emotion analysis, this paper proposes a risk identification model, which classifies the investment platforms with more negative answers into the category of big risks and the investment platforms with more positive answers into the category of small risks. It is suggested that investors can choose investment platforms with small risks for trading. In this paper, BiLSTM is used to study text semantic information, and attention mechanism is used to enhance semantic learning

Table 3 Named entity recognition output

Question	Named entity
有人投过律信智投嘛? (in Chinese)	律信智投 (in Chinese)
Has anyone invested in law trust and wisdom? (in English)	Law trust and wisdom (in English)
福彩双色球预测必出号靠谱吗? (in Chinese)	福彩双色球 (in Chinese)
Does the double chromosphere prediction work? (in English)	Double chromosphere (in English)
有人投过泰然金融么?怎么样? (in Chinese)	泰然金融 (in Chinese)
Has anyone invested in poised finance? How's that? (in English)	Poised finance (in English)

of keywords. The input of the word encoding layer is the word vector of the answer sentence of Q&A text. BiLSTM model is used to encode the time step of the answer sentence into the context-related word vector in the semantic learning layer. The output vectors of the positive and negative LSTM model are integrated as the output vector B_t of BiLSTM at the time which is written as:

$$\vec{h}_t = \overrightarrow{LSTM}(h_{\mathrm{t}-1}, x_t, C_{\mathrm{t}-1}), \tag{12}$$

$$\overleftarrow{h}_t = \overleftarrow{LSTM}(h_{t+1}, x_t, C_{\mathrm{t}+1}), \tag{13}$$

$$B_t = \vec{h}_t \oplus \overleftarrow{h}_t . \tag{14}$$

The output of BiLSTM is averaged as the output of semantic learning layer, which is written as:

$$output_{semantic} = \frac{\sum_1^T B_t}{T}. \tag{15}$$

The purpose of the attention layer is to assign a weight to the word encoding vector, to obtain the most informative representation of the current text. Keywords and non-key words in the text have different influences on the text semantics, and keywords in the text tend to reflect whether the investment is risky or not. To strengthen the role of these keywords in the classification, this paper adopts the attention mechanism to study the weight distribution of different words in the text. They are written as:

$$v_t = \tanh(Wx_t + b), \tag{16}$$

$$a_t = \frac{\exp(v_t A)}{\sum_{t=1}^T \exp(v_t A)}, \tag{17}$$

where a_t indicates the importance of the word to the current text, $v_t A$ is automatically learned from the corpus by the model as A scoring system, A and W are weight matrices, and b is a bias matrix. After obtaining the weight of each word, it is assumed that the number of words in the sentence is T and the sum of the word vectors according to the weight is taken as the output of the focus layer. The output is written as:

$$output_{attention} = \sum_{t=1}^{T} a_t x_t . \tag{18}$$

The purpose of the classification layer is to use the integration vector of the semantic learning layer and focus layer to classify and adopt softmax classification, and the result is a probability, which is used to identify the “high risk” and “low risk” situation. This layer takes as input the result integration of the semantic learning layer and the focus layer, which is written as:

$$input_{classify} = output_{semantic} \oplus output_{attention}. \tag{19}$$

Output and probability are written as:

$$output = W_c\, input_{classify} + b_c, \tag{20}$$

$$p_k = \frac{\exp(output_k)}{\sum_{k=1}^{K} \exp(output_k)}. \tag{21}$$

In the above equations, W_c is the weight matrix, b_c is the bias matrix, and K is the number of categories (K = 1, 2) with 1 for “high risk” and 2 for “low risk”. Finally, the label with the highest probability serves as the final classification result.

In the last step, we output the combined text of the named entity of the question text and the risk identification result of the answer text, as shown in Table 4.

3.4 Model training

We use the cross-entropy loss function to train the model. Specifically, the input training data set (x_t, y_t) is the Q&A text to be predicted. y_t is the real label of the x_t. The model is represented by a black box. The output of the model is a vector representing the probability of each category. The goal of the training is to minimize the following loss function:

$$J(\theta) = -\sum_{t=1}^{N} \sum_{k=1}^{K} y_t^k \cdot \log \sigma(x_t) + \frac{\lambda}{\mu} \|\theta\|^2, \tag{22}$$

where N is the number of training samples and λ is the L_2 regularization of the bias parameter.

Table 4 Output text

Named entity	Risk analysis result
律信智投 (in Chinese) Law trust and wisdom (in English)	Low risk
福彩双色球 (in Chinese) Double chromosphere(in English)	High risk
泰然金融 (in Chinese) Poised finance(in English)	Low risk

4 Experiments and results

4.1 Dataset

P2P EYE is an authoritative third-party organization in the Chinese online loan industry. It provides online loan data, online loan information, BBS exchange, and other services for the majority of online loan investors. This paper collected 42,590 Q&A pairs from the question-and-answer section of "everyone is answering". First, we were able to get through the Q&A pairing layer to obtain 30,356 valuable Q&A pairs. Then, NER (Named Entity Recognition) was used to identify the investment platform in the questions of the Q&A text. Besides, we use machines to mark the risk in the answers according to the emotional analysis of the text. Inspired by the existing literature (e.g., Yuan et al. 2018; Singh et al. 2017; Cheng and Jin 2019; Bag et al. 2019), texts with positive emotions are marked as low risk and texts with negative emotions are marked as high risk, as shown in Table 5. Subsequently, we selected 30,000 of them (6000 with high risk and 24,000 with low risk) and divided the 30,000 data into the training set, verification set, and test set, as shown in Table 6.

4.2 Parameter setting

Jieba is a better word segmentation module for Python. Word2vec is a model for generating word vectors. It solves dimensional explosion and the sparse problem of previous word vectors. Liu et al. (2019) to find the best answer to farmers' questions through processing the accumulated agricultural question and answer data. They used Jieba to segment the words and word2vec to form word vectors in data preprocessing. In our experiment, the Jieba tool was used for word segmentation, and Word2vec was used to pre-train the word vectors. All models were built using the deep learning open source framework Tensorflow. All the hyperparameters in the model were adjusted by the performance of the training set. The number of BiLSTM units was set to 200. The number of attention mechanism units was also set to 200. The batch size was set to 64. The learning rate of the optimizer was set to 0.01, and the learning rate was updated by each round of parameters attenuated to 0.8 times that of the previous round. Epochs were set to 60. When the accuracy did not exceed the current highest accuracy within 10 rounds, the model would stop learning early. (All parameter settings were based on previous experience and model training process).

4.3 Evaluations metrics

In many previous studies, the standard Precision, Recall, F1 value, Accuracy are adopted as the evaluation standards (e.g., Wang et al. 2019a, b). In this paper, these indexes are also selected as the evaluation criteria of the model (subscript yes and no mean high risk and small risk respectively).

TP: number of "high risks" in the correct classification;
FP: number of "high risks" in the misclassification;
TN: number of "low risks" in the correct classification;

Table 5 Data set tag

Question	Answer	Risk tag
有人投过律信智投嘛? (in Chinese)	我朋友在这上投资, 说这平台是合法合规的, 在工商局可以查询到的。平台信息透明度很高, 不会像别的平台故意藏着掖着, 而且资金回款到账的时间也很快, 他投了一年的时间, 收益很不错。 (in Chinese)	Low risk
Has anyone invested in law trust and wisdom? (in English)	My friend invests in this, say this platform is legal and compliant, can inquire in industrial and commercial bureau. The information transparency of the platform is very high, and it will not be deliberately hidden like other platforms. Moreover, the time of fund return to the account is also very fast. He invested for one year, and the income is very good (in English)	
福彩双色球预测必出号靠谱吗? (in Chinese)	所谓预测, 也只是根据自己的主观想法所做的一些猜测, 实际上并没有足够的依据, 所以准确率也没办法保证。 (in Chinese)	High risk
Does the double chromosphere prediction work? (in English)	The so-called prediction is only some guesses made according to one's own subjective ideas, but actually there is not enough basis, so the accuracy is not guaranteed (in English)	
有人投过泰然金融么?怎么样?	我投过泰然金融, 挺靠谱的, 平台全透明, 回款和提现的时间很快, 近期准备复投, 还介绍给了身边的朋友, 他们试了之后都说收益的效果很好, 跟我说这个平台挺靠谱的~(in Chinese)	Low risk
Has anyone invested in poised finance? How's that? (in English)	I have invested in poised finance, which is quite reliable. The platform is completely transparent, and the time for receiving and withdrawing money is very fast. Recently, I prepared to reinvest and introduced it to my friends (in English)	

Table 6 Data set partition

Number	Training set (18,000)	Verification set (6000)	Test set (6000)
High risk (6000)	3600	1200	1200
Low risk (24,000)	14,400	4800	4800

FN: the number of "low risks" in the misclassification.

$$Precision_{yes} = \frac{TP}{TP + FP}, \tag{23}$$

$$Precision_{no} = \frac{TN}{TN + FN}, \tag{24}$$

$$Recall_{yes} = \frac{TP}{TP + FN}, \tag{25}$$

$$Recall_{no} = \frac{TN}{TN + FP}, \tag{26}$$

$$F1_{yes} = \frac{2 * Precision_{yes} * Recall_{yes}}{Precision_{yes} + Recall_{yes}}, \tag{27}$$

$$F1_{no} = \frac{2 * Precision_{no} * Recall_{no}}{Precision_{no} + Recall_{no}}, \tag{28}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \tag{29}$$

4.4 Comparative models

We use the following existing models for comparative purposes to evaluate the performance of our proposed model. The model description is shown in Table 7.

4.5 Results

This experiment was conducted on the CPU server. Running the model on the CPU server can process a large amount of data faster. First, the training set of 18,000 data points was used for model learning, then the verification set of 6000 data points was used to further improve the model, and finally, the test set of 6000 data points was used to test the risk identification effect of the final model. The experimental results are shown in Table 8.

As Table 5 demonstrates, for most metrics including precision, recall, F1-score and accuracy, the proposed model is the best in the risk identification of the Q&A text. CNN can convert a sentence into a two-dimensional matrix through a word vector method for

Table 7 Model description

Model	Reference	Experiment
CNN	Guo et al. (2019) used CNN for text classification. They used word embeddings with different weights for semantic learning and then used CNN classification	The experiment uses CNN to extract sentence features and finally applied softmax to classify risks
CNN + attention	Shrivastava et al. (2019) proposed a model for applying attention mechanisms to CNN to detect the emotions from the text with good precision and accuracy score	After learning sentence semantics, the attention layer assigns different weights to words in the experiment
RNN	Lee et al. (2019) used RNN for analyzing medical reports. They built a system that uses RNN to automatically identify fracture and nonfracture cases	The experiment uses RNN for sentence semantic learning
RNN + attention	Jang et al. (2019) employed the document information vector by RNN and the self-attention mechanism to find the semantic space of the sentence. It becomes possible to better capture the global latent feature of the sentence	In the experiment, the attention mechanism is added to the RNN to enhance semantic expression
LSTM	Song et al. (2019) used LSTM to improve the accuracy of the automatic translation of English subtitles	The LSTM is used for semantic learning and average the output corresponding to each input as a sentence expression
LSTM + attention	Deng et al. (2019) applied attentional mechanisms in LSTM for emotional analysis	In the experiment, the attention mechanism is added to the LSTM to enhance sentence semantic expression
BiLSTM	Makarenkov et al. (2019) utilized a BiLSTM for learning the proper word choice based on a word's sentential context	In the experiment, BiLSTM is used to fully learn the context information
BiLSTM + attention	Cai et al. (2019) adopted attentional mechanisms in BiLSTM to extract the interaction between questions and answers	After semantic learning, BiLSTM adds an attention mechanism to learn the meaning of keywords

Table 8 Comparison of experimental results of each model

Model	High risks			Low risks			A
	P	R	F1	P	R	F1	
CNN	76.08	43.17	55.08	74.96	92.61	82.86	75.18
CNN + attention	77.58	44.87	56.86	76.17	93.15	83.81	76.45
RNN	75.25	42.98	54.71	75.04	92.38	82.81	75.08
RNN + attention	77.16	44.43	56.39	75.88	93.00	83.57	76.13
LSTM	78.33	44.98	57.17	76.04	93.35	83.81	76.50
LSTM + attention	79.25	45.74	58.00	76.50	93.65	84.21	77.05
BiLSTM	81.75	47.55	60.13	77.46	94.44	85.11	78.32
BiLSTM + attention	80.92	47.67	60.00	77.79	94.22	85.22	78.42

natural language processing. This paper uses CNN to conduct a text risk analysis as a comparative model. Since the nodes between each layer of CNN are connectionless, it is often helpless to model sequential data. CNN + Attention model adds an attention mechanism to CNN, which can effectively learn the key semantics of sentences, so the final model's recognition effect is better than CNN. The nodes between the hidden layers of RNN are connected, which can model the dependence between the data at different moments in the sequence data, remember the past information, and learn strong semantic expression.

However, RNN has a severe gradient dissipation phenomenon, which makes it difficult to learn the long-range dependence of answers in the Q&A text. Our Q&A text is mostly long, so RNN does not work very well. The recognition effect is significantly enhanced when RNN introduces the attention mechanism. LSTM is a special structure type of RNN that adds three control units of the input gate, output gate, and forget gate, which can solve the problem of long sequence dependence in neural networks.

Finally, the classification effect is obviously improved, and semantic learning is enhanced by adding the attention mechanism. But LSTM only considers the positive sequence information. This paper adopts the BiLSTM that consists of two positive connection LSTM by increasing the reverse sequence information acquisition and fully considering the influence of the context information of the current output, which helps obtain a more comprehensive semantic understanding of the text. After joining the attention mechanism, through different weights on a different time step, we can focus on words that have a significant impact on the sequence to enhance semantic understanding, and thus obtains a more accurate output and achieve a better effect.

5 Conclusion

Investors need to choose a relatively reliable investment platform when entering the investment market. Even though risks are everywhere, we can still avoid risks and gain benefits through some analysis. The development and operation of a platform cannot be separated from the supervision of risks, and the supervision of the financial industry by the government cannot be separated from the analysis of risks. Our research proposes a model to help conduct risk analysis. We summarize the theoretical and practical contributions as well as the limitations and future research opportunities as follows.

5.1 Theoretical contribution

This paper proposes text risk analysis based on the existing text emotion analysis. This paper uses advanced text processing machine learning and artificial intelligence technology to mine and analyze the Q&A text data on the online loan platform and tries to dig out relevant financial risk information based on peer theory. Aiming at addressing the problem of identifying risks in online lending investment from text data, this paper constructs a model for risk identification of the Q&A text based on attention mechanism and BiLSTM. This model is used to identify the risk of the Q&A text on an online lending platform. This model is better than other existing models in terms of many metrics. This paper uses hot deep learning technology in recent years to study the identification of risk in fintech. Combined with the advantages of each technology for final risk detection, the model improves the accuracy and precision of risk identification.

5.2 Practical contribution

According to the research method in this paper, investors can avoid the dilemma between limited manpower and the need to obtain risk knowledge about investment platform quickly and comprehensively. According to the risk identification results obtained, the high-risk investment product means that the previous investors do not respond well to this product, which may be risky, or this product is not likely to earn returns. The low-risk product means that experienced investors think it is worth buying and can earn a profit. According to the experience and knowledge of the predecessors reflected in these question-and-answer texts, new investors can choose to invest in less risky platforms, and to a large extent avoid risks to obtain returns. For the investment platform, this method can be used to find out the investment products that may have some problems, analyze the causes of the problems, and solve the corresponding problems, to better manage their platform to achieve the sustainable development. For relevant government agencies, they can focus on high-risk platforms according to the risk identification results obtained, to supervise their operations, find out possible risks, and provide better supervision for the P2P industry.

5.3 Limitations and prospects

However, there are still some limitations to this study. The emotional analysis of the data set in this paper does not take into account the impact of extreme emotions on the results. Future work will consider removing these extreme speech texts to obtain more accurate risk identification results. In this paper, the size of risks is simply identified by dichotomy. Future studies need to consider the identification of various risk categories. The experimental part of this study also has shortcomings. The data set used in this study has a category imbalance problem, which may have a certain impact on the model's effectiveness. Future research should focus on the problem of unbalanced data set classification. We plan to further study the problem of risk management based on risk identification.

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