

Application of Improved Convolution Neural Network in Financial Forecasting

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ABSTRACT

Financial status and its role in the national economy have been increasingly recognized. In order to deduce the source of monetary funds and determine their whereabouts, financial information and prediction have become a scientific method that cannot be ignored in the development of national economy. This paper improves the existing CNN and applies it to financial credit from different perspectives. Firstly, the noise of the collected data set is deleted, and then the clustering result is more stable by principal component analysis. The observation vectors are segmented to obtain a set of observation vectors corresponding to each hidden state. Based on the output of PCA algorithm, the authors recalculate the mean and variance of all kinds of observation vectors and use the new mean and covariance matrix as credit financial credit and then determine the best model parameters. The empirical results based on specific data from China's stock market show that the improved convolutional neural network proposed in this paper has advantages and the prediction accuracy reaches.

KEYWORDS

Convolution Neural Network, Data Discretization, Financial Credit, Principal Component Analysis

1. INTRODUCTION

In recent years, the Internet financial industry in China has grown explosively. With the development of science and technology and the improvement of data complexity in financial market, deep learning model is more suitable for large, high-dimensional and streaming data in financial market. The characteristics of data features not only enhance the application of predictive analysis method in the field of financial risk management, but also focus on the establishment of experimental research paradigm from linear to nonlinear parameters, focusing on model structure and dynamic characteristics. The results from experienced fields have well grasped tail risk, which to a certain extent promotes the development and improvement of relevant financial risk management theories. However, the application of deep learning faces many problems, such as program error, subjective judgment error and insufficient financial supervision. Therefore, you should reasonably use the deep learning model in the field of financial risk management.

With the continuous development of the industry, how to effectively carry out financial forecasting has become one of the key links of the sustainable and healthy development of the Internet financial industry, which has attracted people's attention. In reference (Liu et al., 2019), a multi-scale coupling carbon price prediction method based on unstructured data manifold learning is proposed. Firstly, the unstructured data related to carbon price is extracted by web search index, and the dimension is

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reduced based on isometric mapping manifold learning. He then used the first mock exam (EMD) to decompose the other factors and structured data of the carbon trading price into variable number of unique mode functions (IMF). Based on the precise rough method, the IMF is reconstructed into high frequency sequence, low frequency sequence and trend term. We also use Arima and neural network to predict high frequency data, low frequency data and trend term. But the accuracy of the forecast is not high. Yu Xu et. al (2019) interest rate information from financial derivatives is usually used to predict changes in interest rates, tiee-28 swaps are used to predict changes in monetary policy in Mexico, and a series of financial variables are used for risk correction. We evaluated whether the risk adjusted model is superior to the tiee-28 swap rate, and found that the variability described in the sample was improved when the risk adjusted model was used. From a central point of view, compared with the direct use of tiee-28 exchange, the sample external prediction of the main model recorded is similar in the short term, but it is much better statistically in the long term. Dimitrios Bellos et al (2019) applying a model for capturing the dynamics of financial volatility is proposed, which is called lstm-sv model. The proposed model overcomes the short-term memory problem of the existing SV model, captures the nonlinear dependence of potential fluctuations, and generally has better external prediction performance than SV model. Simulation study provides strong evidence for the long-term memory of stock index data.

Convolutional neural network (CNN) is a feedforward neural network with excellent image processing performance, which has been widely used in image classification and location. Compared with other neural network structures, convolution neural network requires relatively few parameters, so it is widely used. Po-Chen Lin et al(2019)faced the problem of determining the corresponding relationship between two images consistent with geometric models such as affine or thin plate spline transformation and estimating their parameters is solved, and a convolutional neural network architecture for geometric matching is proposed. It imitates the standard steps of feature extraction, matching, anomaly detection and model parameter estimation, and supports end-to-end training. Meanwhile, the first mock exam can not only annotate the network parameters from the synthesized images without manual annotation, but also greatly improves generalization ability. Therefore, there is no image at all, and the same model provides the latest results for the instance level and the thorny flow dataset. Category level matching is provided. Amish Jahangir Kapoor et al (2019), a pattern recognition technology based on machine learning is proposed to solve the problem of vortex beam detection by different angular momentum (OAM), which provides a new method for multi OAM state detection. The phase screen of numerical simulation based on the improved power spectrum inversion method of von Karman is used to study the recognition rate of different OAM beams under different wavelength, transmission distance and atmospheric turbulence through CNN (convolutional neural network) model. Power spectrum model.

The results show that CNN trained by a powerful turbulence database can be more accurate in all kinds of turbulence conditions, while the hybrid training database can improve the accuracy in other turbulence conditions. These results are helpful to the demultiplexing system of free space optical OAM system. In the current development trend, convolutional neural network is developing, and will generate convolutional neural network for various application scenarios, such as 3D convolutional neural network for video understanding. It is worth noting that the convolutional neural network is not only applicable to image related networks, but also includes image like networks, such as the chessboard analysis (Gutta et al., 2019; Sun et al., 2019).

In order to solve the problem of credit risk assessment in Internet banking industry, a customer credit assessment method based on circuit neural network is established, which uses data discretization, key component analysis and circuit neural network. The evaluation model of board of directors firstly divides the input data into dynamic data and static data, and transforms the dynamic data and static data into matrix and vector respectively, then uses the improved circuit neural network to automatically extract, classify and introduce the circuit. Neural network structure can predict financial time series data(Du et al., 2019; Wang et al., 2019). Firstly, this paper summarizes the research methods of

financial time series at home and abroad, introduces the artificial neural network and deep learning method briefly, and focuses on the algorithm principle of convolutional neural network and principal component analysis. Then the convolution neural network is improved on the financial time series data, and a hybrid model of convolution neural network and principal component analysis is established. Finally, the two prediction models are applied to the prediction of financial time series data.

The main research work of this paper is as follows. (1) Inspired by the WaveNet model, CNN combines the features of the proposed financial time series data, and uses the relu activation and parameterized skip link of the network model used to predict the stock index prediction results to simplify and optimize the time series prediction. In order to study the influence of related parameters, a new and better adjustment method is used. (2) The exchange rate prediction model based on convolution neural network is established, and the exchange rate prediction results are predicted by using the model parameters. In order to improve prediction accuracy. Application of hybrid convolution neural network principal component analysis hybrid prediction model in exchange rate prediction (3) for quantitative transactions, it is assumed that there is a specific pattern in time series data, which is related to the nature of financial information and can be understood in time. CNN can extract potential patterns, and through simulation and comparison, we can determine the validity and validity of the two prediction models. Explain that the establishment of the model is effective. In general, we prove that the circuit network is easier to train than the recurrent network, and in the nonlinear and noisy prediction tasks, compared with the recurrent network, it can achieve at least the same or better accuracy.

2. METHODS

2.1. Convolutional Neural Network

In reference (Peng et al., 2019), a CNN based multi-layer feature fusion strategy based on cascading layer is proposed. The new method is evaluated in the public data set of Pascal VOC. The experimental results show that the CNN attracts more attention than the traditional artificial neural network. Study it. In machine learning, convolutional neural network (CNN) is a feedforward neural network, in which artificial domain neurons can respond to specific surrounding cells in the service area, and are used for speech recognition, image processing and image recognition(Goceri, 2019).

$$a_j^l = f \left(\sum_{i \in M_j^l} a_i^{l-1} * k_{ij}^l + b_j^l \right) \quad (1)$$

Where f is the activation function, is the number of network layers, b is the input feature map set, is the j -th feature map of the layer convolution layer, is the convolution core, is the offset. For the activation function, l is the number of network layers, M is the input feature mapping set, a is the j th feature mapping of the convolution layer, K is the convolution kernel, and B is the offset (Zhao et al., 2019).

At the lower sampling level, after the input feature is operated, the output feature mapping becomes smaller, but the number does not change.

$$a_j^l = f \left(\beta_j^l \text{down}(x_j^{l-1}) + b_j^l \right) \quad (2)$$

Downsampling is about reducing the size of data. The training of convolutional neural network can be divided into two stages: forward and reverse. In the forward propagation stage, samples are

obtained from the sample set, and X is used as the input of the convolution neural network to convert the input layer to the output layer.

We are now focused on updating the BP of the convolution layer in the network (Nagata et al., 2019). In the convolution layer, the function diagram of the previous layer is interwoven with the learnable convolution kernel, and then the output function can be obtained by the enable function. Each output map can be a value that convolutes a combination of multiple input maps.

$$x_j^l = f(\sum_{i \in M_j} x_i^{l-1} * k_{ij}^l + b_j^l) \quad (3)$$

Where M_j is the selected input mapping set. Which input graph is selected? You can choose one or three. However, the following describes how to automatically select feature drawings that need to be connected. Each output graph provides an additional offset B , but for a specific output graph, the convolution kernel that makes up each input graph is different. In other words, if the output characteristic graph J and the output characteristic graph K are summed from the convolution in the input graph I , the corresponding convolution kernel is different.

In order to effectively calculate the sensitivity of layer L , we need the sensitivity map corresponding to the upper sampling upsample and the lower sampling downsample layer (each pixel in the feature map corresponds to a sensitivity, so it also constitutes a map). In this way, the sensitivity map size is consistent with the map size of the convolution layer, and then the partial derivative of the activation value of the map of layer L is compared with that of layer $L + 1$. The sensitivity map of the upper sampling layer is multiplied by each element (Zhang et al., 2019).

The weight of map in the lower sampling layer is the same value α , and it is a constant. So we only need to multiply the result of the previous step by one α to calculate the sensitivity δ of the first layer.

We can repeat the same calculation process for each feature map J in the convolution layer. But it is obvious that the map of the corresponding sub sampling layer needs to be matched:

$$\delta_j^l = \alpha_j^{l+1} (f'(u_j^l) \circ up(\delta_j^{l+1})) \quad (4)$$

$Up(.)$ indicates an up sampling operation. If the sampling factor of down sampling is n , it simply copies each pixel horizontally and vertically n times. This will restore the original size. In fact, this function can be realized by Kronecker product:

$$up(x) \equiv x \otimes 1_{n \times n} \quad (5)$$

For a given map, we can calculate its sensitivity map (Kim, 2019). Then we can quickly calculate the gradient of the basis of bias by simply summing all nodes in the sensitivity map in layer L :

$$\frac{\partial E}{\partial b_j} = \sum_{u,v} (\delta_j^l)_{uv} \quad (6)$$

Finally, BP algorithm (formula (5)) can be used to calculate the slope of convolution kernel weight. In addition, many connected weights are shared, so for a given weight, you need to evaluate the gradient of all connected points (connections of shared weights) connected to the weight, and then evaluate the gradient. Similar to the gradient based calculation above:

$$\frac{\partial E}{\partial b_j} = \sum_{u,v} (\delta_j^l)_{uv} (p_i^{l-1})_{uv} \quad (7)$$

Here, $(p_i^{l-1})_{uv}$ is in convolution x_i^{l-1} and k_{ij}^l . The value of the (U, V) position of the output convolution map is the result of the multiplication of the (U, V) position of the previous layer and the convolution kernel k_{ij}^l . For the above formula, the convolution function of Matlab can be used:

$$\frac{\partial E}{\partial k_{ij}^l} = \text{rot180}(\text{conv2}(x_i^{l-1}, \text{rot180}(\delta_j^l, 'valid')))) \quad (8)$$

We first rotate the delta sensitivity map, so that we can do cross-correlation calculation, rather than convolution (in the mathematical definition of convolution, the characteristic matrix (convolution kernel) needs to be flipped when it is passed to conv2)(Baghersalimi et al., 2019; Li & Wang, 2019). That is, reverse the rows and columns of the feature matrix). Then we reverse the output, so that when we convolute the forward propagation, the convolution kernel is the direction we want.

2. 2 Data Discretization

Reference (Namanja et al., 2019) adds standardization items to limited data to ensure stability, while standardization items only consider data defects (noise). The numerical simulation of acoustic wave propagation usually needs to discretize the imaging region based on many assumptions. This can eliminate part of the noise. For example, the speed of sound in tissue is constant and therefore incomplete. In this task, you perform discrete data mining analysis to get the data (Saukani & Ismail, 2019). This can be divided into two types. One is continuous quantitative characteristic, which represents some measurable characteristics of the described object. Its value comes from continuous intervals such as temperature, length, etc. Discrete qualitative attributes are discretization of continuous attributes, whose values are represented by language or some discrete values.

A decision table is a set of attributes, called a set of conditional attributes, called a set of decision attributes, and a domain. Let the number of decision types be. A breakpoint on the value field of the property can be recorded as, where C is the real set. Any set of breakpoints on the value field defines a classification on,

$$P_a = \left\{ [c_0^a, c_1^a), [c_1^a, c_2^a), \dots, [c_{k_a}^a, c_{k_a+1}^a) \right\} \quad (9)$$

$$l_a = c_0^a < c_1^a < c_2^a < \dots < c_{k_a}^a < c_{k_a+1}^a = r_a \quad (10)$$

$$V_a = [c_0^a, c_1^a) \cup [c_1^a, c_2^a) \cup \dots \cup [c_{k_a}^a, c_{k_a+1}^a) \quad (11)$$

Therefore, a new decision table is defined arbitrarily. After discretization, the original information system is replaced by a new one.

2. 3. Principal Component Analysis

Key component analysis is a commonly used dimension reduction algorithm in data mining, whose main purpose is to reduce the dimension(Pashazadeh & Javan, 2019). You can also extract and use the maximum individual differences displayed by key components. Similar to factor analysis, reduce the number of variables in regression and cluster analysis.

There are many factors that affect a person's credit rating, such as the number of investors and the amount of financial investment. The commonly used methods to study the factors influencing the results of each variable include multiple regression, principal component analysis, factor analysis and regression classification tree. Each algorithm has its own characteristics. In this paper, we choose the main component analysis method.

Key component analysis: PCA combines multiple indicators into a group of new and unrelated comprehensive indicators. These indicators should reflect the total indicators as little as possible to reflect the original indicator information. Methods of analysis. Because the variance of the first principal component of the method is the largest of all the original variables, the variance of the comprehensive evaluation function will never exceed the variance of the first principal component, so the method has some defects. So to solve this defect.

- (1) There are six factors that affect the comprehensive ability of financial credit, which are the classification and clustering of target market customers, the analysis of customer behavior, the design and construction of data warehouse for multidimensional data analysis and data mining, and the total number of financial categories. Set the influencing factors as $a_1, a_2, a_3, \dots, a_n$. Their comprehensive index, namely, the principal component, is set as: z_1, z_2, \dots, z_m ($m < P$) Then

$$z_1 = l_{11}a_1 + l_{12}a_2 + \dots + l_{1p}a_p \quad (12)$$

$$z_m = l_{m1}a_1 + l_{m2}a_2 + \dots + l_{mp}a_p \quad (13)$$

They are the original variable indicators z_1, z_2, \dots, z_m . First is $a_1, a_2, a_3, \dots, a_n$, and the second is the m-th principal component.

- (2) Standardize the original data

Because the dimensions of the original data are different, in order to make the data of different dimensions operate, the data is standardized. With random variables $a_1, a_2, a_3, \dots, a_n$, whose sample mean is recorded as $\bar{a}_1, \bar{a}_2, \bar{a}_3, \dots, \bar{a}_n$, the sample standard deviation is recorded as $S_1, S_2, S_3, \dots, S_n$. First, make a standardized transformation

$$a_i = \frac{\bar{a}_i - a_i}{S_i} \quad (14)$$

- (3) Calculate correlation coefficient matrix, corresponding eigenvalue $\lambda_1, \lambda_2 \dots \lambda_n$ (arranged from small to large) and its corresponding eigenvectors

$$R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \dots & \dots & \dots & \dots \\ r_{n1} & r_{n2} & \dots & r_{nn} \end{bmatrix} \quad (15)$$

- (4) Calculation of principal component contribution rate and cumulative contribution rate

principal component . The contribution rate is:

$$\frac{\lambda_n}{\sum_{k=1}^a \lambda_k} (n = 1, 2 \dots n) \quad (16)$$

The cumulative contribution rate is:

$$\frac{\sum_{k=1}^n \lambda_k}{\sum_{k=1}^a \lambda_k} (n = 1, 2 \dots n) \quad (17)$$

Generally, the characteristic value with cumulative contribution rate of about 85% is taken $\lambda_1, \lambda_2 \dots \lambda_m$, corresponding to the first and second, . . . , $m(m \leq n)$ Principal components(Yan et al., 2019).

3. EXPERIMENTS

3. 1 Data Preparation

(1) Data preparation

1. Data function selection defines input and output variables for financial asset price modeling and self-learning, and some preprocessing of data can improve the accuracy and completeness of financial forecasts. The feature selection mechanism of data (also known as feature subset selection) attempts to determine variables independent of modeling data, and transforms the original feature set into data with low dimensional features. The function of data function selection is to delete irrelevant functions, reduce the overload and excess risk calculation of machine learning (Lv et al., 2020; Yeh & Chen, 2020), and improve the accuracy of prediction. In the reference, there are several types of input variables used to model financial asset prices. The basic analysis provides the macro and micro economic characteristics of the company and the whole market, such as company size, capital, price return, cash flow, leverage, profitability, etc. Technical analysis provides a set of technical attributes, such as moving average, volatility,

balance, momentum and relative strength indicators (Lu et al., 2019; Song et al., 2019). The data source for this article contains data from 50000 users. First, preprocess the data. Categorical variables such as gender are converted to one key coding, while continuous variables such as income amount are standardized (Ding et al., 2019; Feng & Han, 2019). User behavior records and default user attributes are transformed into matrices and vectors respectively, which are used as CNN's input. At the same time, feature extraction is used to extract features from user behavior records as the input of existing algorithms, and feature values are summarized from user behavior records. The selected summary indicators are total number, quantity and average value. In order to better evaluate the model, the data are divided into training set, verification set and test set (Aprausheva & Sorokin, 2019; Tabak et al., 2019).

3.2. Data Denoising

- (1) Classification and clustering of targeted marketing customers. For example, customers with the same savings and payment repayment behavior can be divided into a group. Effective clustering and collaborative filtering methods help to identify customer groups and promote the target market.
- (2) Customer value analysis. Customer segmentation is usually used before customer value analysis, and after segmentation, key customers will be identified according to the "2-8 principle". In other words, 20% of the customers who create 80% of the bank's value provide the best service. In general, key customer discovery is realized through a series of data processing technologies (such as data processing, transformation process, artificial intelligence and artificial intelligence). Analyze the application frequency of customers and the sustainability of financial products to identify customer loyalty, analyze transaction data in detail to identify the detailed customers who want to retain the bank, and find out the common characteristics of customers lost due to mining (Xu, Nelson, & Kerr, 2019). Before losing customers with similar characteristics, please carry out targeted treatment.
- (3) Customer behavior analysis. After you find key customers, you can perform customer behavior analysis, discover customer behavior preferences and customize customized services for customers. Customer behavior analysis includes complete behavior analysis and group behavior analysis. The overall behavior analysis is used to discover the behavior of existing customers in the enterprise. At the same time, the cross mining and analysis of different customer groups enables you to find the rules that change between customer groups, and automatically input customer feedback into the data warehouse through the data cleaning and centralization process of the data warehouse. The understanding of customers and the discovery of customers' behavior law enable the company to formulate its market strategy.
- (4) Design and construct data warehouse for multidimensional data analysis and data mining. For example, you may want to report changes in debt and revenue by month, region, Department, and other factors, along with statistics such as maximum, minimum, sum, and average. Data warehouse, data cube, multi-functional and search based data cube, function, comparative analysis and outlier analysis all play an important role in financial data analysis and mining.
- (5) Loan repayment forecast and customer credit policy analysis (Xu et al., 2020). There are many factors that affect the calculation of payment effect and customer credit rating. Data mining methods, such as feature selection and attribute correlation calculation, can help you identify important factors without excluding them. For example, factors related to payment repayment risk include payment rate, payment term, debt ratio, payment income ratio, customer income level, education level, residence and credit record. Among them, income repayment rate is the main factor, education level and debt ratio are not. Banks can adjust their payment policies accordingly to send payments to previously rejected applications, but an analysis of key factors shows that the underlying information indicates that the risk of the application is relatively low.

Table 1. Principal component analysis results

Eigenvalues: (Sun = 6, Average = 1)					
Number	Value	Difference	Proportion	Cumulative value	Proportion
1	2.160886	0.957194	0.4322	2.160886	0.432221
2	2.03692	0.306993	0.2407	3.364578	0.6729
3	0.896699	0.1793	4.261277	0.85234	0.253939
4	0.400368	0.496331	4.757608	0.9515	0.0993
5	0.2407	0.1793	0.306993	0.957194	0.4322
6	2.1608865	2.160822	0.4323	3.364528	0.6129

The financial management process of the Internet accumulates a large number of customer information resources, and has important commercial value. When criminals obtain and use information, it may lead to a variety of fraud. At the same time, the application of big data leads to longer business chain, imperfect legal system, lack of corresponding legal big data talents, increasing the complexity of data analysis, and facing inevitable legal risks for future development.

- (6) Business association analysis. Association analysis analyzes hidden networks in databases. The bank stores a lot of customer transaction information. By mining and analyzing customers' income level, consumption habits, purchase types and other indicators, potential customer needs can be found. Banks can act as intermediaries between manufacturers and consumers by mining information about corporate customers, and intervene with manufacturers to develop and determine consumer needs, so as to better serve your customers (Aprausheva & Sorokin, 2019).

4. RESULTS AND DISCUSS

4. 1 Data Reduction Analysis

First of all, big data company's data graph analysis, flow processing technology and crawler technology are used to obtain and analyze various customers' online and offline information resources, comprehensively understand and master the actual situation of customers, and quickly and effectively obtain credibility. Describe and use big data credit scoring model to accurately determine the credit status of customers. Secondly, the use of big data resources and big data analysis technology for lending, post loan and fraud risk prevention, pay attention to the transaction status of loan customers, cash flow chain, capital transactions, overdue repayment or default, and always identify the dynamic changes of the company where the loan customer is, which has aroused the severity of the consequences of contract and fraud violations, and constitute the post loan management model, and achieves a certain effect.

Through the application of wavelet transform to data denoising, independent wavelet transform and wavelet transform are applied to the preprocessing of financial data, and the independent component analysis and combination of multi-layer perceptron, wavelet transform and multi-layer perceptron are analyzed respectively (DeBoskey & Peter, 2019).

Use the click and spark flow on each page to analyze the total expenditure by age group in real time

For example, in one step, I wrote a Kafka production program to read files from HDFS, generate data at fixed intervals, then read Kafka data using spark streaming for analysis, and write the analysis results to redis.

Figure 1. Data analysis of financial activities of different age groups

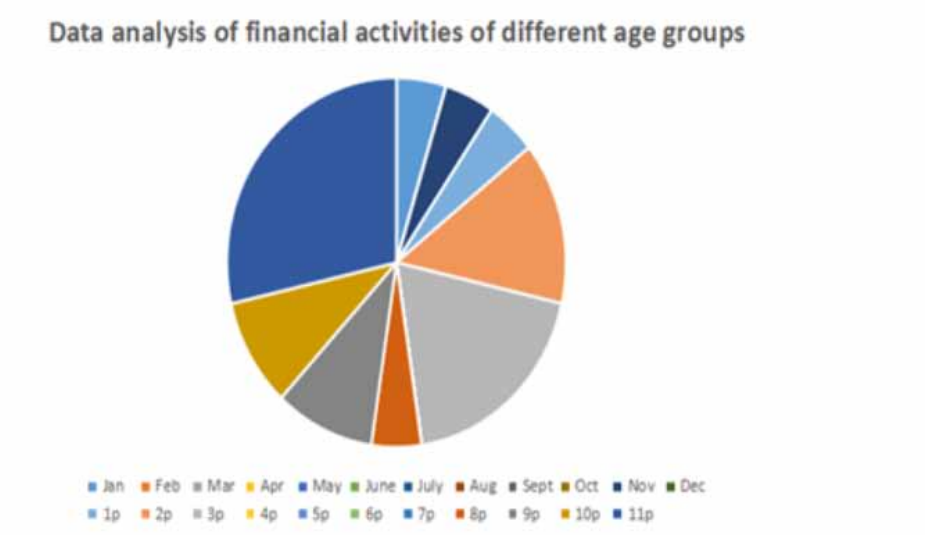
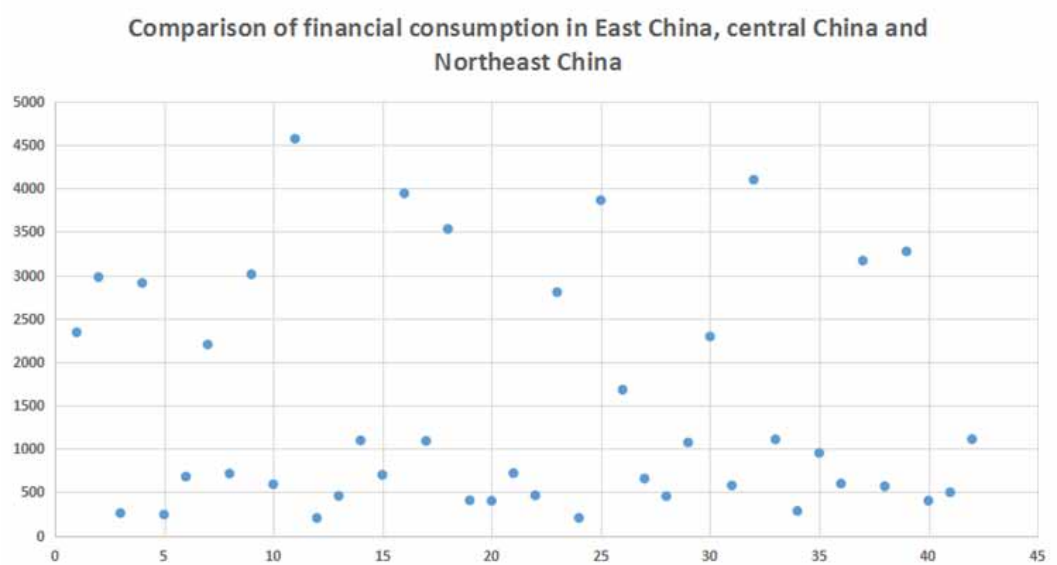
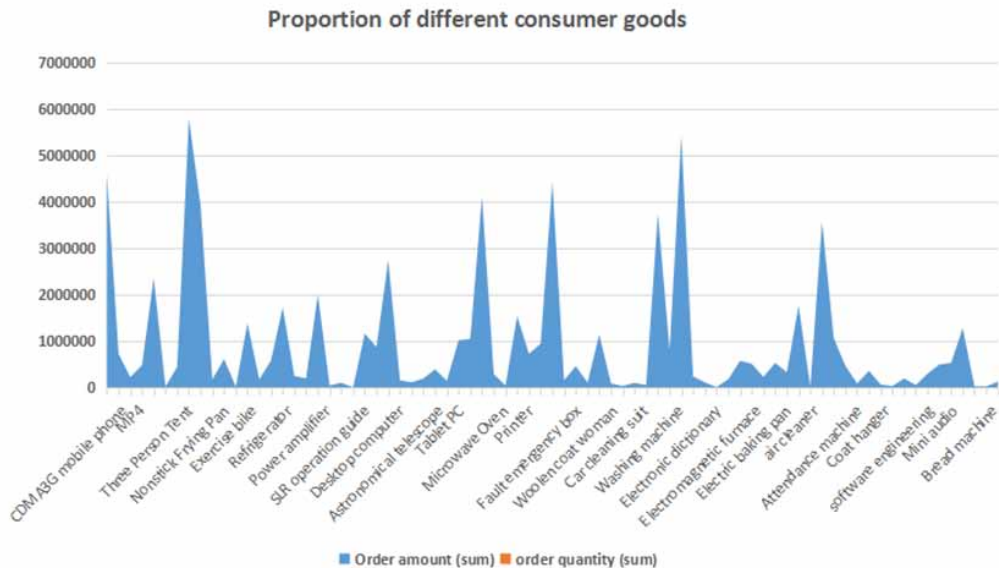


Figure 2. Comparison of financial consumption in East China, central China and Northeast China



- (1) Write the t-click data to the t-click topic of Kafka in turn. The write interval of each data is 10 ms, where uid is the key, and click time + “,” + PID is the value.
- (2) Write the t-order data to the Kafka t - order topic in turn. Each data write interval is 10 ms, where uid is the key, uid + “,” + price + “,” + discount is the value.
- (3) Write a spark flow program, then use Kafka to read and calculate the subject data of t , click.

Figure 3. Proportion of different consumer goods



It accumulates the hits on each page and stores them in redis. The key is “click + PID”, and the value is the cumulative times. Four kinds of noise reduction methods for random walking are combined with a single-layer multi-layer perceptron. The experimental results show that ICA has the best denoising effect in the dataset, and the combined denoising effect of wavelet transform and multi-layer perceptron is the second. In this way, the data analysis that affects the comprehensive ability of credit is clearer.

4. 2 Principal Component Analysis

The six parameters of basic index and liquidity index are analyzed by principal component analysis, and then the convolution neural network algorithm is used to solve the quantitative relationship between these three indexes under the deep learning. Principal component analysis was carried out by SPSS and two principal components were extracted, among which the quantitative relationship between the first principal component, the second principal component and six indexes was as follows:

$$F1=0.42K1+0.713K2+0.143K3-0.269K4+0.721K5+0.537K6$$

$$F2=-0.174K1+0.655K2+0.576K3-0.932K4+0.175K5+0.319K6$$

According to the combination of different index parameters and the comparison of financial forecast results, the accuracy rate is different under the influence of different parameters, as shown in the figure below. Financial consumption includes personal account and personal bank settlement account.

Personal account is a personal account used to process various payment and payment services, such as remittance, remittance, credit card consumption, investment and loan. Company accounts are inter company accounts and cannot be used for credit card consumption and other activities. Personal bank payment account is a bank payment account opened by the depositor in the name of a natural person, with personal identity certificate for investment, consumption, payment, etc. Opening a public account requires many materials, such as a business license and a legal personal certificate. Therefore, it is necessary to distinguish two types of data from the test data.

Figure 4. Comparison of financial behaviors in different regions

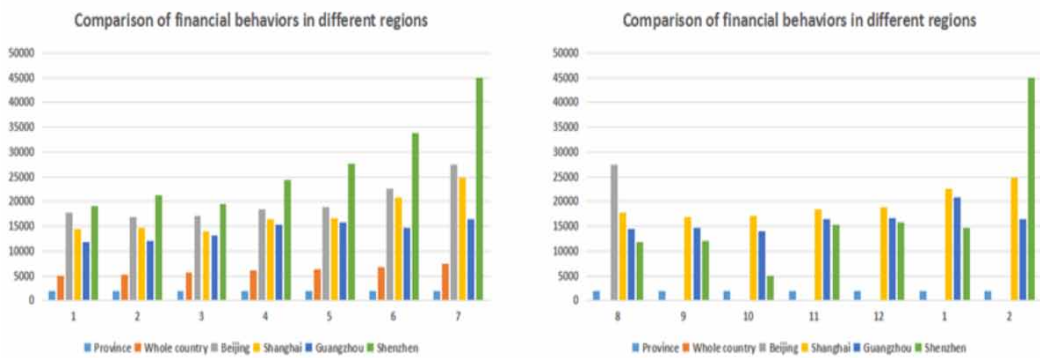
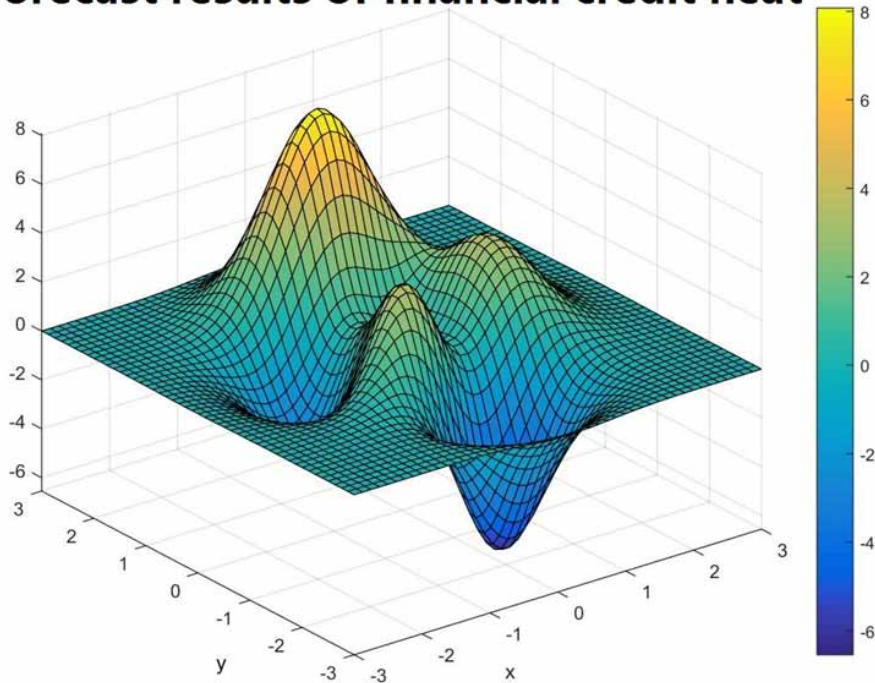


Figure 5. Forecast results of financial credit heat

Forecast results of financial credit heat



4. 3 Convolutional Neural Network for Financial Prediction

By comparing reference (Sun & Du, 2018), we compare data sets under consistent conditions and compare the financial credit forecast results as follows. The correct and reasonable application of deep learning models in the field of financial risk management will help increase the processing speed of

Figure 6. Financial prediction based on convolutional neural network

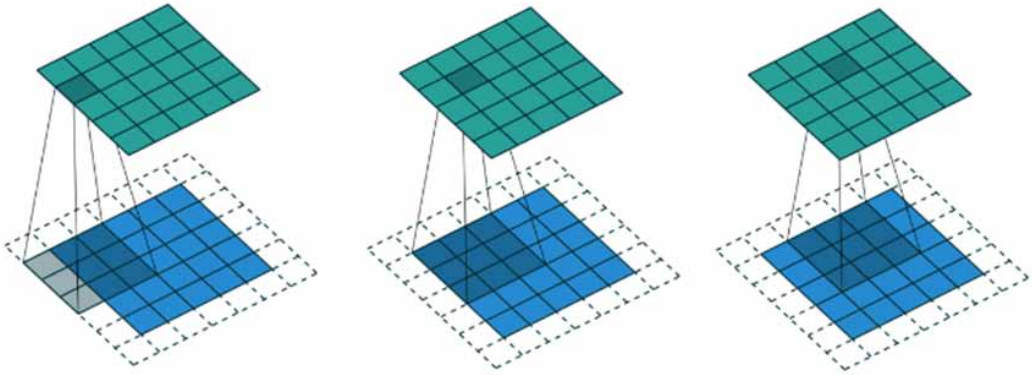
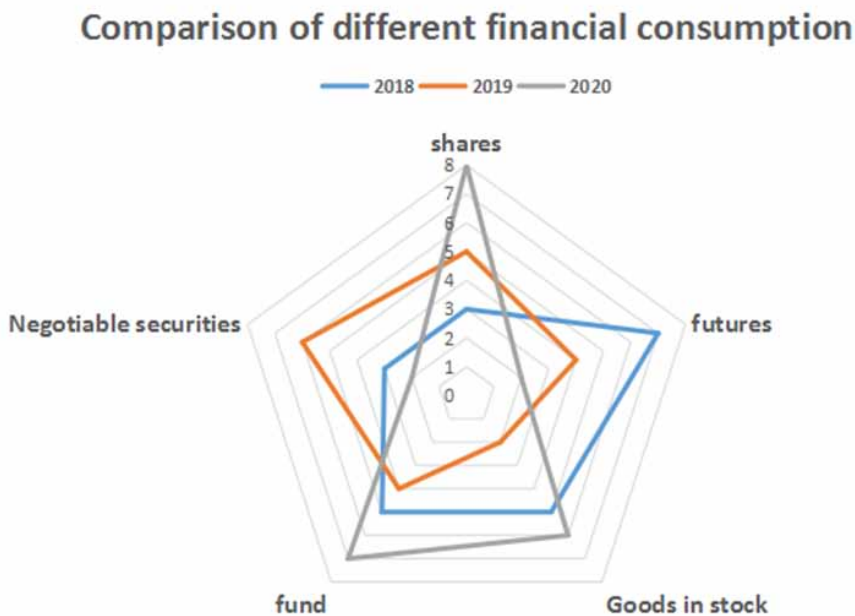


Figure 7. Comparison of different financial consumption



financial data, significantly reduce labor costs, and then promote the improvement of financial risk management process.

At the same time, it is difficult to apply. Therefore, it is very important to discuss how to use the deep learning model reasonably.

The biggest difference between traditional P2P finance and personal consumer finance is the difference between users. Other users may lead to different risk control management. Traditional P2P financial users are mainly small-scale enterprises and individual businesses, but the object of personal consumer finance is individual consumers. Both belong to the category of Internet financial

services, but the loan objectives of the services are quite different. In other words, assets are different. In terms of assets, SMEs and personal consumption, traditional P2P platform investment and asset management funds are usually lent to SMEs that need funds. Therefore, in the current macroeconomic environment, under the background of economic downturn, the survival pressure of small and medium-sized enterprises is gradually increasing. In particular, various social resources are conducive to large companies and restrict the development of small enterprises, and holding companies have become the main factor affecting financial credit prediction. The state continues to encourage the development of small and medium-sized enterprises, but with little success, this situation will continue as the domestic economy enters the “new normal” (Elhoseny et al., 2019).

5. CONCLUSION

The rapid development of financial engineering enriches risk management technology, but it can not completely eliminate financial risks. Aiming at financial risk control, this paper summarizes and analyzes the related research status of financial engineering theory, risk measurement, financial prediction and financial risk control. The evaluation and prediction models established in this paper are simple and practical, which can accurately and quickly predict the future market indicators. The in-depth learning algorithm is used to calculate the valuation indicators, fundamental indicators and liquidity indicators. This model can also be applied to other evaluation and prediction models. At the same time, the data rate set for the entire input vector directly affects the final result. This ratio is related to the selected training area and the way the input vector is constructed. Many experiments are needed to accumulate experience, and understanding the nature of the data can produce good predictions. This article has the insufficiency of in-depth understanding of the theoretical knowledge of financial risk, but the forecast model proposed in this article for financial risk forecasting has certain reference value for future risk forecasting.

REFERENCES

- Aprausheva, N. N., & Sorokin, S. V. (2019). Recognition of Unimodality and Bimodality of a Two-Component Gaussian Mixture with Different Variances. *Pattern Recognition and Image Analysis*, 29(2), 252–257. doi:10.1134/S1054661819020032
- Baghersalimi, S., Bozorgtabar, B., Schmid-Saugeon, P., Ekenel, H. K., & Thiran, J.-P. (2019). DermoNet: Densely linked convolutional neural network for efficient skin lesion segmentation. *EURASIP Journal on Image and Video Processing*, 2019(1), 71. doi:10.1186/s13640-019-0467-y
- Bellos, D., Basham, M., Pridmore, T., & French, A. P. (2019). A convolutional neural network for fast upsampling of undersampled tomograms in X-ray CT time-series using a representative highly sampled tomogram. *Journal of Synchrotron Radiation*, 26(3), 839–853. doi:10.1107/S1600577519003448 PMID:31074449
- DeBoskey, D. G., & Peter, R. (2019). Gillett. Another Look: The Impact of Multi-dimensional Corporate Transparency on US Firms' Market Liquidity and Analyst Forecast Properties. *Review of Pacific Basin Financial Markets and Policies*, 22(3), 1950008. doi:10.1142/S0219091519500085
- Ding, S., Qu, S., Xi, Y., & Wan, S. (2019). Stimulus-driven and concept-driven analysis for image caption generation. *Neurocomputing*. Advance online publication. doi:10.1016/j.neucom.2019.04.095
- Du, Lu, & Fu. (2019). Palm vein recognition based on end-to-end convolutional neural network. *Nan fang yi ke da xue xue bao*, 39(2), 207-214.
- Elhoseny, M., Bian, G.-B., Lakshmanaprabu, S. K., Shankar, K., Singh, A. K., & Wu, W. (2019, August). Effective Features to Classify Ovarian Cancer Data in Internet of Medical Things. *Computer Networks*, 159(4), 147–156. doi:10.1016/j.comnet.2019.04.016
- Feng, Z., & Han, W. (2019). Seismic Signal Blind Denoising Based on W-Weighted Nuclear Norm Minimization. *Jiguang Yu Guangdianzixue Jinzhan*, 56(7), 071503. doi:10.3788/LOP56.071503
- Goceri, E. (2019). Diagnosis of Alzheimer's Disease with Sobolev Gradient Based Optimization and 3D Convolutional Neural Network. *International Journal for Numerical Methods in Biomedical Engineering*, 35(7), e3225. doi:10.1002/cnm.3225 PMID:31166647
- Gutta, Bhatt, & Kalva. (2019). Modeling errors compensation with total least squares for limited data photoacoustic tomography. *IEEE Journal of Selected Topics in Quantum Electronics*.
- Kapoor, A. J., Fan, H., & Sardar, M. S. (2019). Intelligent Detection Using Convolutional Neural Network (ID-CNN). *IOP Conference Series. Earth and Environmental Science*, 234, 012061. doi:10.1088/1755-1315/234/1/012061
- Kim, B. (2019). Image-based concrete crack assessment using mask and region-based convolutional neural network. *Structural Control and Health Monitoring*, 26(6).
- Li & Wang. (2019). Identifying Overlapping Successive Events Using a Shallow Convolutional Neural Network. *IEEE Transactions on Power Systems*.
- Lin, Sun, & Kung. (2019). FloatSD: A New Weight Representation and Associated Update Method for Efficient Convolutional Neural Network Training. *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*.
- Liu, Guo, & Chen. (2019). Multi-scale combined forecast of carbon price based on manifold learning of unstructured data. *Kongzhi yu Juece*, 34(2), 279-286.
- Lu, J., Tang, Y., & Cheng, J. (2019). Analysis and optimization of Turgo hydraulic turbine based on orthogonal experiment design. *Paiguan Jixie Gongcheng Xuebao*, 37(1), 38–42.
- Lv, Z., Zhang, S., & Xiu, W. (2020, March 20). Solving the Security Problem of Intelligent Transportation System With Deep Learning. *IEEE Transactions on Intelligent Transportation Systems*. Advance online publication. doi:10.1109/TITS.2020.2980864
- Nagata, F., Tokuno, K., Mitarai, K., Otsuka, A., Ikeda, T., Ochi, H., Watanabe, K., & Habib, M. K. (2019). Defect detection method using deep convolutional neural network, support vector machine and template matching techniques. *Artificial Life and Robotics*, 24(4), 512–519. doi:10.1007/s10015-019-00545-x

- Namanja, A. T., Xu, J., Wu, H., Sun, Q., Upadhyay, A. K., Sun, C., Van Doren, S. R., & Petros, A. M. (2019). NMR-based fragment screening and lead discovery accelerated by principal component analysis. *Journal of Biomolecular NMR*, 73(12), 675–685. doi:10.1007/s10858-019-00279-9 PMID:31541395
- Pashazadeh, A., & Javan, M. (2019). Improvement of lumped models in multiple inflows rivers by principal component analysis and reliability analysis. *Acta Geophysica*, 67(4), 1–13. doi:10.1007/s11600-019-00290-6
- Peng, J., Kang, S., & Ning, Z. (2019). Residual convolutional neural network for predicting response of transarterial chemoembolization in hepatocellular carcinoma from CT imaging. *European Radiology*, (5), 1–12. PMID:31332558
- Saukani, N., & Ismail, N. A. (2019). Identifying the Components of Social Capital by Categorical Principal Component Analysis (CATPCA). *Social Indicators Research*, 141(2), 141. doi:10.1007/s11205-018-1842-2
- Song, Zhou, & Tan. (2019). Process Monitoring via Key Principal Components and Local Information Based Weights. *IEEE Access*.
- Sun & Du. (2018). Graph-Regularized Fast and Robust Principal Component Analysis for Hyperspectral Band Selection. *IEEE Transactions on Geoscience & Remote Sensing*, 1-11.
- Sun, L., An, W., Liu, X., & Lyu, H. (2019). On developing data-driven turbulence model for DG solution of RANS. *Chinese Journal of Aeronautics*, 32(8), 1869–1884. doi:10.1016/j.cja.2019.04.004
- Tabak, A., Sevimli, K., Kaya, M., & Çağlar, B. (2019). Preparation and characterization of a novel activated carbon component via chemical activation of tea woody stem. *Journal of Thermal Analysis and Calorimetry*, 138(6), 9–10. doi:10.1007/s10973-019-08387-2
- Wang, H., Huang, W.-F., Fang, Y., Zhang, R., Wang, D., Zhan, Q., & Liu, Q. H. (2019). Efficient and Accurate Electromagnetic Modeling of Triaxial Induction Responses From Multiscale Fractures for Well-Logging Applications. *IEEE Journal on Multiscale and Multiphysics Computational Techniques*, 4, 20–28. doi:10.1109/JMMCT.2019.2892944
- Xu, Nelson, & Kerr. (2019). Modeling Temporal Variation in Physical Activity Using Functional Principal Components Analysis. *Statistics in Biosciences*, (6846).
- Xu, X., Cao, D., Zhou, Y., & Gao, J. (2020). Application of neural network algorithm in fault diagnosis of mechanical intelligence. *Mechanical Systems and Signal Processing*, 141, 106625. doi:10.1016/j.ymsp.2020.106625
- Xu, Y., Li, D., Wang, Z., Guo, Q., & Xiang, W. (2019). A deep learning method based on convolutional neural network for automatic modulation classification of wireless signals. *Wireless Networks*, 25(7), 3735–3746. doi:10.1007/s11276-018-1667-6
- Yan, S.-F., Ma, B., & Zheng, C.-S. (2019). Wear localization and identification under nonlinear condition monitoring data. *Journal of Jilin University*, 49(2), 359–365.
- Yeh, J.-Y., & Chen, C.-H. (2020, July 16). A Machine Learning Approach to Predict the Success of Crowdfunding Fintech Project. *Journal of Enterprise Information Management*. Advance online publication. doi:10.1108/JEIM-01-2019-0017
- Zhang, Xu, & Mou. (2019). A Convolutional Neural Network for the Detection of Asynchronous Steady State Motion Visual Evoked Potential. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*.
- Zhao, J., Guo, W., Zhang, Z., & Yu, W. (2019). A coupled convolutional neural network for small and densely clustered ship detection in SAR images. *Science China. Information Sciences*, 62(4), 42301. doi:10.1007/s11432-017-9405-6

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