Exploring the Landscape of Financial Deep Learning: Models, Applications and Future Directions

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Abstract. With the rapid development of artificial intelligence and financial technology, the application of machine learning, especially deep learning, in the financial field has aroused strong research interest. In order to explore the application field of financial deep learning, the literature of financial deep learning in the past ten years is summarized, and the model introduction and application field are respectively summarized. The results show that the models commonly used in financial deep learning include convolutional neural networks, recurrent neural networks and long short-term memory neural networks, and they have a wide range of applications in financial text analysis, financial risk assessment and anomaly detection, and portfolio management. In the future, new text mining and natural language processing techniques can be applied to the field of behavioral finance for more in-depth research, while more possibilities for applying deep learning to emerging financial areas such as cryptocurrencies and blockchain can also be explored.

Keywords: Deep learning; The financial sector; Neural network; Text analysis; Risk assessment; Portfolio management

1 Introduction

With the development of artificial intelligence in China, the amount of literature is also increasing rapidly. Stock market prediction, financial risk assessment, and portfolio management are the most important problems to be solved. In the field of machine learning, deep learning is an emerging field. This paper first introduces the most commonly used deep learning models in the financial field, including Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and recurrent neural network (CNN). RNNand Long Short-Term Memory (LSTM). Then, the application of deep learning in the financial field is introduced in detail by collecting and sorting out relevant literature. Finally, it summarized and analyzed the challenges and development prospects.

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2 Deep learning models in finance

A deep learning model is a complex architecture with multiple layers of neural networks that can progressively extract high-level features from the input. In recent years, the most widely used deep learning models in the financial field mainly include convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and its variants Long Short-Term memory network (LSTM). Timing diagram of deep learning models is shown in FIG 1.The application research in the field of financial data analysis has been deepened. These advanced artificial intelligence technologies can not only mine the deep rules hidden behind the massive financial time series data, effectively predict market trends, asset pricing, and transaction behavior analysis, but also be used to build complex financial decision-making systems to cope with dynamic changes in the investment environment.

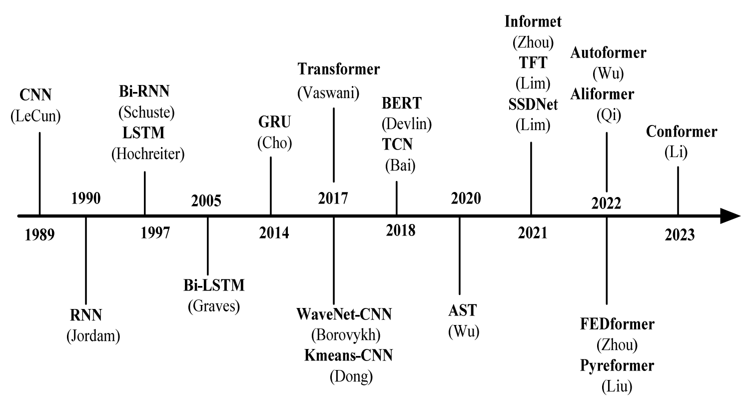

Fig. 1. Timing diagram of deep learning models

2.1 Convolutional Neural Network (CNN)

In deep learning, CNN algorithm[1] was first proposed, which can directly extract the features in the picture and classify the information in the picture through the computer itself. The CNN algorithm mainly extracts the feature information in the picture through the convolution calculation layer. Activation functions can help solve nonlinear problems; Pooling was used to reduce the parameters of the model, improve the speed of the algorithm, and prevent the appearance of over-fitting of the model algorithm. Finally, it used the Fully Connectedlayers (FC) to classify the required information in the image. Compared with traditional machine learning, CNN algorithm has better classification effect and fewer network model parameters.

The typical CNN architecture is first stacked with multiple sets of convolutional layers and pooling layers, and then a feed-forward neural network composed of several fully connected layers is superimposed. The last layer outputs the prediction value through different activation functions. With the increase of convolutional layers, the network structure also becomes deeper, the input image becomes smaller, and has more feature maps [2]-[4]. Based on the basic architecture of CNN, there are many improved architectures that have achieved significant performance improvement, including AlexNet, LeNet, VGG, GoogleNet, ResNet, SENet, etc. LeNet-5, created by LeCun in 1998 , is a convolutional neural network that has achieved remarkable results in handwritten character recognition. The LeNet-5 architecture, shown Table 1.

Table 1. Lenet-5 architecture description

Layer	Types	Dimension	Nuclear size	Step size	Size	Activation function
Input layer	Input	1	–	–	32×32	–
C1	Convolution	6	5×5	1	28×28	tanh
S2	AvgPooling	6	2×2	2	14×14	tanh
C3	Convolution	16	5×5	1	10×10	tanh
S4	AvgPooling	16	2×2	2	5×5	tanh
C5	Convolution	120	5×5	1	1×1	tanh
F6	FullyConnected	–	–	–	84	tanh
Output layer	FullyConnected	–	–	–	10	RBF

AlexNet was developed by Alex et al. And achieved a top-5 error rate of 16% in the ImageNetILSVRC Challenge in 2012, much lower than the second place error rate of 26%. AlexNet is very similar to LeNet-5 with the main improvements being a deeper architecture with larger kernels, and AlexNet is the first architecture to stack convolutional layers directly on top of each convolutional layer instead of stacking pooling layers on top of each convolutional layer. In addition, AlexNet uses the ReLU activation function instead of the traditional sigmoid function, and applies a dropout layer with a 50% loss rate to the output of the fully connected layer to reduce overfitting. The architecture of AlexNet is shown in Table 2.

Table 2. AlexNet architecture description

Layer	Types	Dimension	Nuclear size	Step size	Size	Activation function
Input layer	Input	3(RGB)	–	–	224×224	–
C1	Convolution	96	11×11	4	55×55	ReLU
S2	MaxPooling	96	3×3	2	27×27	–
C3	Convolution	256	5×5	1	27×27	ReLU
S4	MaxPooling	256	3×3	2	13×13	–
C5	Convolution	384	3×3	1	13×13	ReLU
C6	Convolution	384	3×3	1	13×13	ReLU

C7	Convolution	256	3×3	1	13×13	ReLU
F8	FullyConnected	–	–	–	4096	ReLU
Output layer	FullyConnected	–	–	–	1000	Softmax

2.2 Long Short-Term Memory Network (LSTM)

Long - Short Term Memory (LSTM) [5] , That is a kind of time recurrent neural network . The main innovation of LSTM compared with RNN is the addition of the gate structure of memory unit state and three control unit state, namely inputgate, forgetgate and outputgate. When there is a new input, if the input gate is activated, its information will accumulate into the cell. At the same time, if the forget gate is open, the past cell state may be forgotten in the process. The output gate further controls whether the latest cell output will be propagated to the final state. An advantage of using memory cells and gate control cells is that the gradient will be controlled in the cell and can prevent the gradient from disappearing too quickly. These additional units enable the LSTM architecture to learn long-term temporal dynamics that cannot be achieved by RNN, becoming a network architecture with a stabilizing effect for modeling long-range dependencies. Stacking multiple LSTMS can be concatenated over time to form more complex structures for training. The basic LSTM unit is shown in FIG 2.

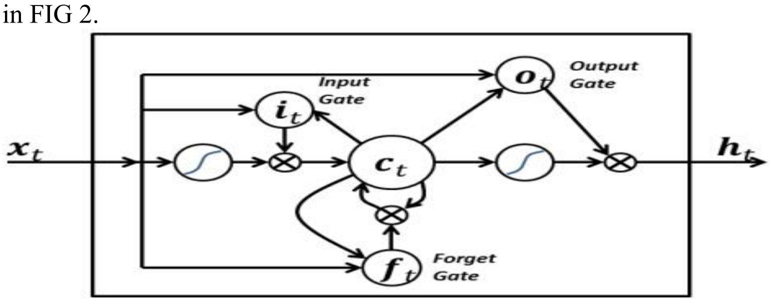

Fig. 2. Diagram of the LSTM computation

LSTM solves the drawbacks of RNN, such as vanishing gradient and not supporting long-term memory problems, by introducing a gating mechanism. The advantage of LSTM network is that it can remember short-term and long-term values in the network, so it is widely used in sequence data analysis such as automatic speech recognition, language translation, handwritten character recognition, and time series data prediction.

2.3 Recurrent Neural Network(RNN)

Recurrent neural network (RNN) is a special kind of neural network with self-connected structure in deep learning, which can learn complex vector to vector mapping. RNN are mainly used to process time series data, including sequence data such as audio, speech and language, and are composed of continuously structured RNN units combined with RNN structures of previous states, as shown in FIG 3. Artificial Neural Network (ANN)[6] models used in traditional predictive analytics are not suitable for sequential data because they treat each input as an independent entity, whereas observations in sequential data are not independent of each other. Unlike other feedforward networks, RNNS use internal memory to process incoming inputs, and during their operation, process sequence data one by one. Notably, it takes into account the time factor of processing elements in the sequence, using hidden states to keep previously processed observations and use them in the next one that will be processed. Thus, the output in an RNN depends not only on the current input, but also on the output computed from the previous hidden state of the network.

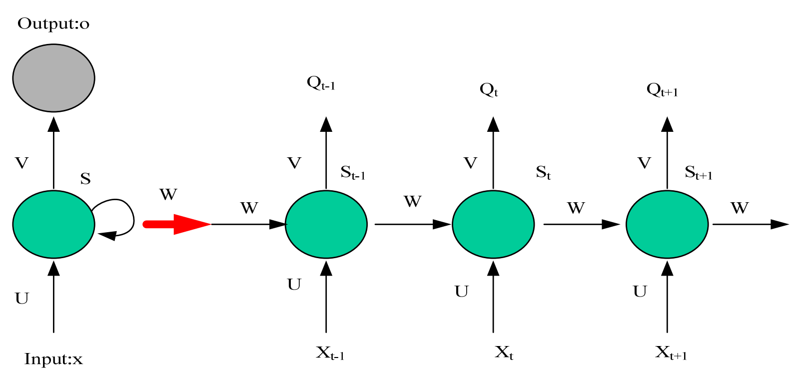

Fig. 3. Diagram of RNN computation

The special structure of RNN makes it have the following two advantages: first, it can model sequence input vectors of arbitrary length; Secondly, the information before and after each time step can be taken into account when processing sequential data. The information in RNNS is propagated through loops, which allows the model to use the same parameters, thus reducing the complexity of parameters. The drawback of RNN is that it does not support long-term memory and faces the vanishing gradient problem.

3 Application of Deep Learning in finance

3.1 Financial text mining

With the rapid spread of social media and real-time news media, instant text-based information retrieval has also been applied to financial model development. A lot of useful information can be obtained by analyzing the context of news, financial statements, company information disclosure, etc. Therefore, financial text mining research has become very popular in recent years. For example, KRAUS et al[7]. implemented an LSTM model with transfer learning using text mining techniques based on financial news and stock market data. Zhang Mengji et al[8]. proposed a news event classification model based on CNN-RNN, and used the LSTM model to predict the trend of individual stocks by combining capital flow and corporate finance.

3.2 Sentiment analysis of financial texts

There is a growing interest in financial sentiment analysis, especially in applying sentiment analysis models using deep learning to financial market prediction. Geng Lixiao et al[9] proposed a sentiment analysis model based on CNN to construct investor sentiment features, and used LSTM model to predict stock trends.

3.3 Anomaly detection

Financial fraud detection, also known as anomaly detection, is a problem that governments all over the world attach great importance to, and it is urgent to develop a good solution. Anomaly detection is one of the most widely studied areas of machine learning. Credit card anomaly detection is one of the most studied problems in this research field. Huang Liangyu et al[10]. proposed an abnormal trading behavior detection method based on network embedding and LSTM model, which can effectively detect abnormal trading behavior in the market.

3.4 Financial risk assessment

The most well-known examples is the 2008 global financial crisis. The mortgage crisis caused by the improper risk assessment of credit default swaps (CDS) among financial institutions led to the bursting of the housing bubble, which in turn led to the Great Depression of the global economy. Applying deep learning to the area of risk assessment can lead to greater accuracy.Wang Zhongren et al[11] . proposed a neural network model combining LSTM and CNN with attention mechanism to score personal credit, so as to improve the accuracy of credit risk assessment. Chen Xuebin et al[12]. used the LSTM neural network method, which is good at dealing with long-term dependencies, to construct a prediction model of Chinese credit bond default risk, and achieved a high prediction accuracy.

3.5 Portfolio Management

Portfolio management is actually an optimization problem, determining the best possible course of action to select the best performing asset in a given period. For the portfolio selection problem, LEE et al .compared three RNN models (S-RNN, LSTM, GRU) for stock price prediction, and then selected stocks according to the prediction to build a threshold based portfolio.

4 Conclusion

CNN use convolutional filters to identify patterns in data and are widely used in the field of image recognition and natural language processing. RNNS are designed to recognize sequential patterns, and they are especially powerful in situations where context is critical, and are therefore often used in sentiment analysis. LSTM network is a special RNN that is able to learn long-term context and dependencies, which compensates for the problem of gradient vanishing and not supporting long-term memory of RNN. The main application areas of deep learning in finance are financial text analysis, anomaly detection, financial risk assessment, and portfolio problems. Among them, financial text analysis is the most researched field, and text mining and sentiment classification are usually used to analyze text information such as financial The development of text mining techniques, natural language processing techniques, and the combination of agent-based computational finance and semantics provides new research opportunities for this research area, which can be further investigated in the future. In addition, with the rise and popularity of some new financial fields, such as cryptocurrency and blockchain technology, their impact on the financial market is also increasing. Applying deep learning innovatively to these emerging financial fields can explore more possibilities for the financial market.

5 Challenges and prospects of deep learning in finance

The development trend and prospect of deep learning in the financial field are very broad. With the continuous development of financial markets and the continuous progress of technology, deep learning will be more and more widely used in the financial field.

On the one hand, the application of deep learning in financial risk control, credit evaluation, fraud detection, anti-money laundering and other fields has achieved remarkable results and will continue to play an important role in the future. At the same time, other applications of deep learning in the financial field will continue to emerge, such as the application of investment strategy optimization, intelligent investment advisory, insurance pricing and so on.

On the other hand, the application of deep learning in the financial field will also face some challenges and problems. For example, how to improve the generalization ability of the model, how to ensure the security and privacy of the data, and how to balance the computing resources and training time. These problems require continuous exploration and research of new methods and techniques to solve.

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