

## *Retraction*

# **Retracted: Data Analysis Deep Learning Research on Spatiotemporal Preposition Construction Network**

### **Wireless Communications and Mobile Computing**

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*Wireless Communications and Mobile Computing* has retracted the article titled “Data Analysis Deep Learning Research on Spatiotemporal Preposition Construction Network” [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process and the article is being retracted with the agreement of the Chief Editor.

### **References**

- [1] W. Guo and Z. Jiang, “Data Analysis Deep Learning Research on Spatiotemporal Preposition Construction Network,” *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 9416747, 11 pages, 2022.
- [2] L. Ferguson, “Advancing Research Integrity Collaboratively and with Vigour,” 2022, <https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/>.

## Research Article

# Data Analysis Deep Learning Research on Spatiotemporal Preposition Construction Network

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Chinese space-time prepositions (CSTPs) are a class of function words used to introduce space-time relations into motion or state, which have experienced the process of evolution from ancient Chinese. In recent years, the research on modern CTSPs shows the trend of grammaticalization research, cognitive semantic research, and research based on constructionalization and lexicalization. At present, there are few studies on the systematic semantic description of CTSPs in cognitive linguistics, and their semantic extension is closely related to the cognitive mechanism. This study is aimed at describing and explaining the functions of CSTPs in constructional networks, aiming to provide clearer semantic information for nonnative language learners. This is a comprehensive study combining qualitative and quantitative analysis. Qualitative analysis includes exploration of cognitive mechanisms, description of semantic networks, misinterpretation, and establishment of lexicographically definition model. Quantitative analysis includes data analysis of the Chinese corpus. The importance of qualitative analysis is far greater than that of quantitative analysis. It does not mean that quantitative analysis is not important. Quantitative analysis is important, and qualitative analysis is relatively more important.

## 1. Introduction

Prepositions are an important category of Chinese parts of speech, and they are also more complex parts of speech. Many scholars have conducted research on Chinese prepositions, studied the definition model of prepositions, the properties of prepositions, and the process and motivation of preposition development, and achieved a lot of results. As a kind of function words, prepositions are used frequently, although they are few in number, and are an important category of function words in the modern Chinese grammar system. The spatiotemporal prepositions are one of the major categories of prepositions, which can represent time

and space components. Data analysis is an effective means to achieve scientific management and statistical participation in decision-making. The data analysis department uses the advantages of abundant data to carry out analysis and research and penetrates into the inner essence of things through the superficial phenomenon of things.

Space-time prepositions are the most representative type of prepositions, and space-time category is the most basic cognitive category of human beings. The looming situation of prepositions will be reflected in space-time prepositions, and the looming situation of box-type prepositions of space-time arguments is more complex and more representative. Therefore, taking spatiotemporal prepositions as the

research topic of this paper, we hope to find the conditions for their use based on the description and induction of the syntactic positions and looming situations of spatiotemporal prepositional phrases and then enhance understanding of the grammatical functions of prepositions.

The innovations of this paper are as follows: (1) it introduces the theoretical knowledge of data analysis deep learning and spatiotemporal prepositional construction network and uses deep learning to analyze how deep learning plays a role in the research of spatiotemporal prepositional construction network. (2) The traditional spatiotemporal preposition construction and the deep learning-based spatiotemporal prepositional construction network are analyzed. Through experiments, it is found that the deep learning-based spatiotemporal prepositional construction network is more conducive to the development of Chinese language.

## 2. Related Work

With the development of deep learning, its application fields are also more and more extensive. Chen et al. found that classification is one of the hottest topics in hyperspectral remote sensing, but they cannot accomplish the task of hierarchically extracting deep features. He applied the concepts of deep learning to it and found that deep learning can obtain the highest classification accuracy from it. Although the method proposed by he is very good, there is no practical example to prove the reliability of the method [1]. O Shea and Hoydis presented and discussed several new applications of deep learning at the physical layer. By interpreting communication systems as autoencoders, he developed a new approach where he incorporated the concept of radio transformer networks as a means of incorporating domain knowledge into machine learning models. He shows the application of convolutional neural networks on raw samples for modulation classification, which is more accurate than traditional schemes that rely on expert features, but he did not explain why the convolutional neural network is more accurate nor did he verify the accuracy of the convolutional neural network [2]. Young et al. found that deep learning thrives in the context of natural language processing. He reviews important models and methods related to deep learning and provides their evolution. He also summarizes and compares various models but does not specifically describe how he provides the evolution of these models [3]. Hou et al. propose a model to fairly measure objective image quality assessment metrics, which directly learns qualitative assessments and outputs numerical values for general use and fair comparison. Images are represented by natural scene statistical features, training a discriminative deep model classifies features into five levels, but he did not explain in detail what the five levels are, making his conclusion unconvincing [4]. Ravi et al. found that with the massive influx of multimodal data, data analytics is playing an increasing role in informatics. This has also prompted a growing interest in generating analytical, data-driven models based on machine learning in informatics. Deep learning, a technology based on artificial neural networks, has emerged

in recent years as a powerful machine learning tool that promises to reshape the future of artificial intelligence. In addition to predictive power and the ability to generate automatically optimized high-level features and semantic interpretations from input data, computational power, fast data storage, and parallelization have also contributed to the rapid adoption of the technology, but he did not clearly describe the advantages of deep learning but made a general generalization [5]. Zhu et al. found that as the core of the shift to data-intensive science, machine learning techniques are becoming more and more important, especially deep learning has proven to be a major breakthrough and an extremely powerful tool in many fields. More importantly, he encourages remote sensing scientists to bring their expertise to deep learning as an implicitly universal model to address unprecedented, large-scale challenges such as climate change and urbanization, but he did not elaborate on how to deal with these large-scale challenges, making the importance of deep learning unsupported [6]. Lo'ai et al. found that mobile cloud computing integrates mobile and cloud computing to extend its capabilities and benefits. He discussed the role of mobile cloud computing and big data analytics in network medicine. With the application of cloud computing in healthcare, he presents the motivation and development of networked healthcare applications and systems, describing an infrastructure for healthcare big data applications. However, his conclusion does not have specific experimental objects and experimental data; so, it is difficult to prove the credibility of the conclusion [7]. Tang et al. found that data-intensive analysis due to various sensors is a major challenge for smart cities. The natural characteristics of geographic distribution require a new computing paradigm to provide location-aware and latency-sensitive monitoring and intelligent control, and fog computing, which extends computing to the edge of the network, meets this need. He introduced a layered distributed fog computing architecture to support the integration of numerous infrastructure components and services in future smart cities. He analyzes case studies using an intelligent pipeline monitoring system based on fiber optic sensors and deep learning algorithms, but he did not give a specific introduction to the case study, and the reliability of the experiment without the case is too low [8].

## 3. The Concept of Deep Learning and Spatiotemporal Prepositions

The Internet has become an indispensable technology in the world today. The Internet regards the earth as the core of the information network. It can not only communicate with friends at any time but also realize resource sharing, cost reduction and efficiency. The network is a shuttle that transcends time and space and is not limited by time and space [9]. The space enables chatting, watching movies, watching news, and other activities. The Internet is a platform with individuality, and wonderful ideas can be developed smoothly on the Internet [10]. The development of the Internet is shown in Figure 1.



FIGURE 1: Development of the Internet.

As shown in Figure 1, language is a social phenomenon that changes with society and evolves with society. With the integration of the world economy, the rapid development of science, and technology and the increase in the frequency of international exchanges, people live in a fast and efficient era [11]. When communicating, people will try to avoid complexity. As a language of communication, Chinese language will naturally develop in the direction of simplicity and convenience.

As a kind of function words, prepositions are small in number but frequently used and are an important function word category in the modern Chinese grammar system. The space-time prepositions are one of the major categories of prepositions, which can introduce a class of prepositions that express time and space components. Construction grammar is a grammar theory that gradually emerged in the late 1980s, and its research methods are adapted to almost all language categories. According to cognitive linguistics, a construction refers to a pattern of form-meaning pair such that the form or function could not predict from the components constructing the pattern [21, 22].

With the ever-closer exchanges between China and other countries and the faster economic development, many people are becoming more and more interested in the Chinese language. The number of people learning Chinese is also increasing. From 2014 to 2018, the number of people learning Chinese and the percentage of growth are shown in Table 1.

As shown in Table 1, among the four major ancient civilizations in the world, only China's culture and history have been inherited. China's history and culture of more than 5,000 years have a long history and have a certain influence on world culture [12]. The Chinese language also promotes the communication and development between countries. Through the study of Chinese language and literature, students can comprehend the profound connotation of literary works and be influenced by the literary essence of "truth, goodness and beauty," so as to have a deeper understanding of the world and life, and thus improve their overall quality.

TABLE 1: Number of people learning Chinese and percentage of growth from 2014 to 2018.

Year	Number of people (thousands)	Percentage	Growth rate
2014	5683	20%	5%
2015	7901	29%	9%
2016	12085	38%	9%
2017	17492	53%	15%
2018	27893	68%	15%

The object studied in this paper is the space-time preposition. The space-time preposition not only introduces the category of time and space but also includes the structure of the preposition to express the time and space. That is to say, the introduced object itself does not represent time or space, but it can represent time and space after adding a preposition [13]. Common prepositions are shown in Figure 2.

As shown in Figure 2, limitations of existing machine learning deep learning are as opposed to shallow learning. Nowadays, many learning methods are shallow structure algorithms, which have certain limitations, such as limited ability to represent complex functions in the case of limited samples, and their generalization ability for complex classification problems is restricted to a certain extent. And deep learning can learn a deep nonlinear network structure. Deep learning is widely used in various fields, which can automatically learn features from input data. With simple nonlinear transformations, more abstract expressions of higher-level input data can also be obtained. In classification studies, through the high-level representation of the data, the ability of the model to distinguish the input data can be enhanced, and the interference of other factors can be reduced. Considering the above characteristics of deep learning models, deep learning models will be applied to the study of spatiotemporal prepositional construction networks [14].

## 4. Neural Network Algorithm Based on Deep Learning

*4.1. Basic Neural Network Algorithms.* For a classifier, the selection of features is very important for its classification results. In many practical problems, it is often not so easy to find those features that are important for classification, or they are not so easy to measure due to the constraints of conditions. Therefore, how to better express features is very important for deep learning [15]. The system structure diagram of deep learning is shown in Figure 3.

As shown in Figure 3, in the field of classification, the use of high-level representation of data can enhance the ability of the classifier to distinguish and exclude other interferences. The features used in the deep learning model are not extracted manually but are learned from the data using a general learning method, which is also the advantage of deep learning [16].

The learning algorithm of deep learning network belongs to unsupervised feature learning, which is based on feature hierarchy. The deep network simulates the thinking

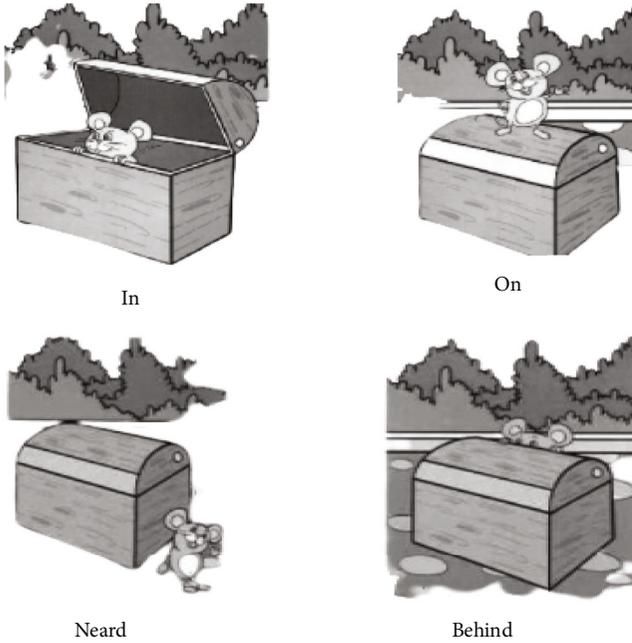


FIGURE 2: Common prepositions.

mechanism of the human brain to interpret data, establishes a deep neural network with analysis and learning functions, and simulates the thinking mode of the human brain to interpret and learn data [17].

Almost all learning algorithms of forward deep networks can be considered as learning algorithms of neurons. When two neurons are excited at the same time, the mathematical expression is shown in formula (1):

$$\Delta w_i = \eta b a_i. \quad (1)$$

Among them,  $\eta$  controls the size of the learning speed, and  $\Delta w_i$  represents the size of the correction to the  $i$ -th weight. The learning of deep networks often starts with unsupervised initialization of weights. First, the unsupervised method is used to obtain the performance of each layer of data with the idea of greedy algorithm, and then the deep network is adjusted by the existing method.

The back-propagation algorithm is usually used as the key method of neural network training, and its basic idea is to input the training samples into the network in the process of learning and training network parameters [18].

For the data whose training sample set is  $\{(a^{(1)}, b^{(1)}), \dots, (a^{(m)}, b^{(m)})\}$ , where  $m$  is the number of samples, the neural network is trained with this sample set. In detail, for a single sample  $(a, b)$ , its cost function is formula (2):

$$J(W, y, a, b) = \frac{1}{2} \|h_{w,b}(a) - b\|^2. \quad (2)$$

Its overall cost function is defined as formula (3):

$$J(W, y) = \left[ \frac{1}{m} \sum_{i=1}^m J(W, y, a^{(i)}, b^{(i)}) \right]. \quad (3)$$

Among them,  $J(W, y)$  calculates the mean square error between the output value and the expected value, and the function of the weight decay parameter  $J$  is to balance the relative importance of the front and rear items in the cost function [19].

The key step of the gradient descent method is to calculate the partial derivative, and its iterative formula is as shown in formula (4):

$$W_{ij} = W_{ij}^{(1)} - \alpha \frac{\partial}{\partial W_{ij}^{(1)}} J(W, b), \quad (4)$$

where  $\alpha$  is the learning rate.

Setting the network loss function as a sign to determine whether the system is stable, such as formula (5):

$$L = \frac{1}{2} \|b - h_{w,b}(a)\|^2. \quad (5)$$

**4.2. Recurrent Neural Network Algorithm.** In recent years, the research of deep network has produced many excellent learning algorithms, among which the learning of forward network is mainly based on the back-propagation algorithm [20]. However, the back-propagation algorithm is easy to make the network learning fall into the local optimum and cannot jump out. Therefore, this paper studies and proposes the recurrent neural network. The structure diagram of the recurrent neural network is shown in Figure 4.

As shown in Figure 4, the bidirectional gated recurrent neural network model (LSTM) is an improved method based on the long-short-term memory neural network model. Compared with the structure of three gates, the LSTM model has only two gates: update gate and reset gate.

In the gradient calculation method in the recurrent neural network, when the number of time steps is large or the time step is small, the gradient of the recurrent neural network is more likely to decay or explode. Usually for this reason, it is difficult for RNNs to capture the dependencies of large time step distances in time series in practice. The gated recurrent neural network is proposed to better capture the dependence of the time step distance in the time series. It controls the flow of information through gates that can be learned. Its structure is shown in Figure 5.

As shown in Figure 5, LSTM adds a mechanism based on a simple recurrent neural network to adjust the network structure and control the information transmission in the neural network. Using LSTMs one can control the amount of information that the memory cell needs, the amount that needs to be discarded, the amount of up-to-date information that needs to be kept in the memory cell, etc. Therefore, LSTMs can learn relatively long-span dependencies while solving vanishing or exploding gradients.

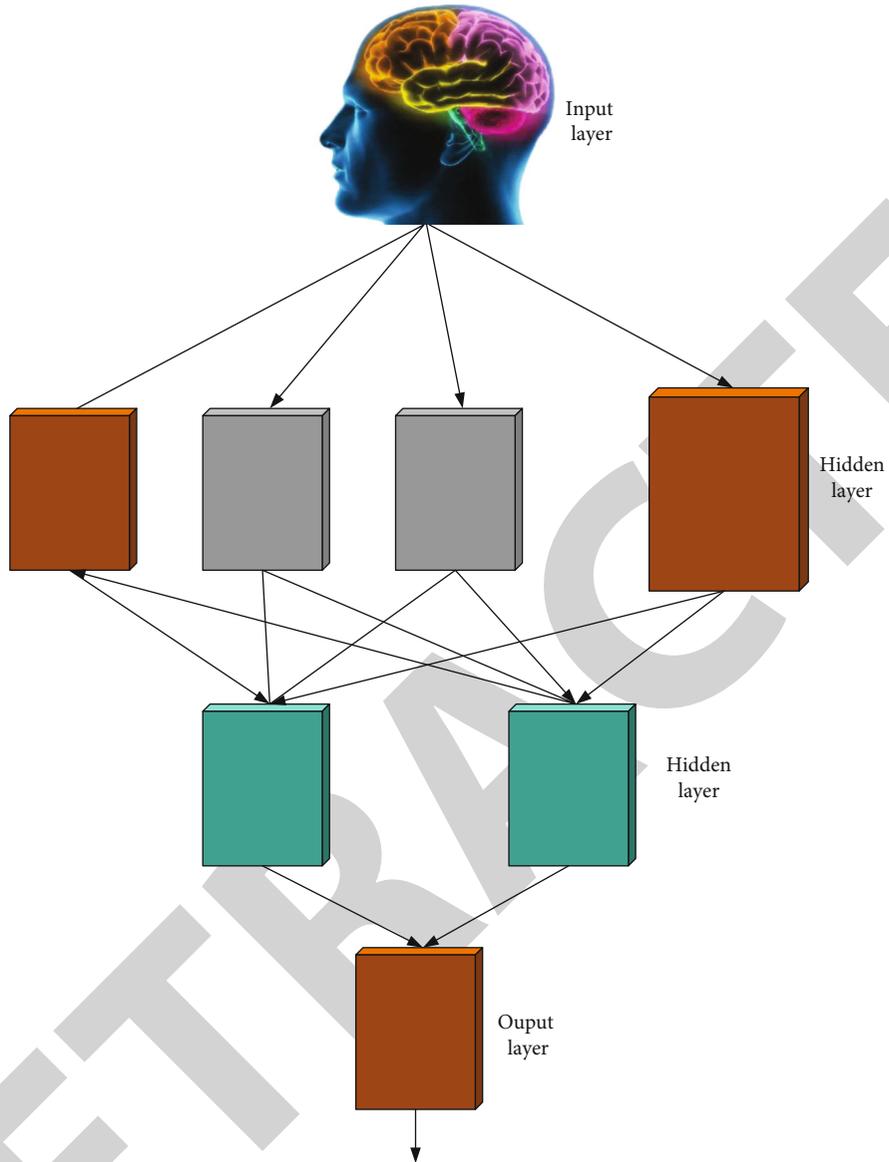


FIGURE 3: System structure diagram of deep learning.

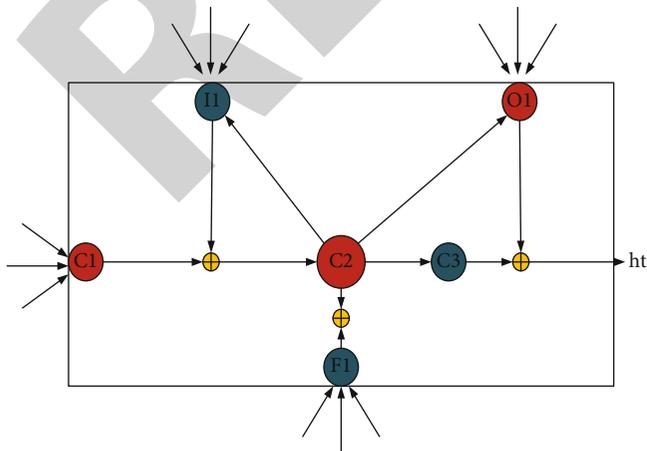


FIGURE 4: Structure diagram of a recurrent neural network.

The expression of the LSTM model is shown in formula (6):

$$z_t = \text{sigmoid}(wa_t + uh_{t-1}). \quad (6)$$

$z_t$  represents the update gate, which is used for the control of input information, and  $a_t$  represents the reset gate, which mainly deals with short-term dependencies. The weight matrix is as formula (7):

$$h_t = \tanh(wa_t + uh_{t-1} \cdot r_t). \quad (7)$$

$h_t$  is the candidate hidden layer, receiving  $[a_t, h_{t-1}]$ , indicating the candidate state of the hidden layer at the current moment, and the candidate hidden layer is as

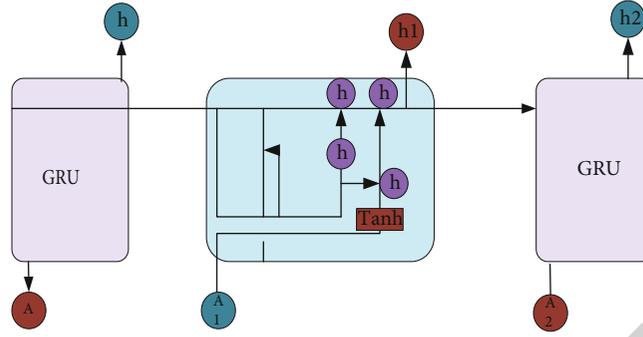


FIGURE 5: LSTM model.

formula (8):

$$h_t = (1-z_t) \cdot h_{t-1} + z_t \cdot h_t. \quad (8)$$

**4.3. Conditional Random Field Model.** In the sentence parsing task, the conditional random field model is implemented by defining characteristic functions and weighting coefficients. In the conditional random field model, the characteristic functions are divided into node characteristic functions and local characteristic functions. The node characteristic function is shown in formula (9):

$$s_l(b_i, a, i), l = 1, 2, 3, \dots, L. \quad (9)$$

For a given parameter  $\lambda = \{\lambda_1, \lambda_2, \dots, \lambda_n\}$ , the conditional random field model defines the conditional probability  $P(b|a)$  of the corresponding state  $B = \{b_1, b_2, \dots, b_n\}$  on the sequence  $A = \{a_1, a_2, \dots, a_n\}$  as formula (10):

$$P(b|a) = \frac{\exp(\sum_{i,k} \alpha_k t_k(b_{i-1}, a) + \sum_{i,k} \beta_k (b_i, a))}{Z(a)}. \quad (10)$$

$B_*$  is the best state among all states, which is formula (11):

$$B_* = \arg \max P(b|a). \quad (11)$$

Precision and recall are two metrics that are widely used in word parsing tasks and are often used to evaluate the quality of task results. The total number of preposition words is  $n_{\text{Total}}$ , the number of correct preposition words is  $n_{\text{Correct}}$ , and the accuracy rate Precision is formula (12):

$$\text{Precision} = \frac{n_{\text{Correct}}}{n_{\text{Test}}}. \quad (12)$$

The recall rate Recall is formula (13):

$$\text{Recall} = \frac{n_{\text{Correct}}}{n_{\text{Total}}}. \quad (13)$$

Simply relying on the accuracy index and recall rate cannot achieve the level of understanding whether the result is good or bad; so, this paper proposes a compre-

hensive evaluation index as formula (14):

$$F = \frac{(a^2 + 1) * P * R}{a^2 * (P + R)}. \quad (14)$$

Usually researchers take 1 for the weight, which is the most common F1 value. The F1 value is formula (15):

$$F1 = \frac{2 * P * R}{P + R}. \quad (15)$$

In order to keep the association information between the words below five characters to the greatest extent, and avoid unnecessary redundancy to the greatest extent, this paper adopts the five-character mark method. On the basis of ensuring accuracy, the time and space complexity of the model training process is significantly reduced. The Chinese vocabulary statistics of the five-character mark method are shown in Table 2.

As shown in Table 2, using LSTM model one-way propagation training to solve the problem of serialization and labeling, to a certain extent, solves the problem of feature extraction of traditional methods. However, the long-distance information obtained by this method is relatively simple, and even the important information is forgotten, which leads to the situation that the word segmentation result is completely irrelevant to the correct word segmentation result.

The time and space complexity of the conditional random field model training process is shown in Table 3:

As shown in Table 3, with the increase of the number of experiments, the training time of the conditional random field model generally shows a downward trend, from 29 seconds to 22 seconds, while the space complexity decreases from 65% to 50%. But overall, the space complexity is still very high. In order to avoid this kind of error, this paper proposes to consider bidirectional propagation training and make full use of the forward long-distance information features and backward long-distance information features to verify the Chinese word segmentation task. And LSTM can meet the advantages of bidirectional propagation training, as shown in Table 4:

As shown in Table 4, the range of expressive ability of LSTM model is 81.7%-89.4%, and the range of modeling

TABLE 2: Chinese vocabulary word count.

Vocabulary type	Number (unit: thousand)	Ratio (%)
Single word	10	5%
Double word	90	56%
Three characters	15	18.2%
Four characters	15	18.2%
Five characters	1.6	1.6%
Six characters and above	0.8	1%

TABLE 3: Time and space complexity of the conditional random field model training process.

Number of experiments	Time (s)	Space complexity
5	29	65%
10	26	57%
15	27	55%
20	25	49%
30	22	50%

TABLE 4: Advantages of LSTM.

Number of experiments	Expression ability	Modeling ability
5	89.4%	79.3%
10	83.6%	80.5%
15	87.0%	78.1%
20	82.54%	75.6%
30	81.7%	74.2%

ability is 74.2%-80.5%. LSTM breaks through the defect of insufficient linear expression ability in traditional NLP tasks. And because of its powerful modeling ability, complex feature data can be obtained without a lot of experiments and experience, it has significant advantages in processing word segmentation, and the robustness of LSTM is also very high.

LSTM is no longer directly solved by scoring vector probability, but considers the linear weighted combination of local features of the entire sentence and uses the conditional random field model to calculate the joint probability. The advantage of this is that the conditional random field model can optimize the entire sequence.

**4.4. Pretrained Vector Layer.** Since the number of part-of-speech tagging sets far exceeds the number of part-of-speech tagging sets, pretraining is particularly important for part-of-speech tagging tasks. In general, the pretrained models have small errors, and as the depth of the neural network increases, the robustness is better, and the average variance is smaller [21, 22].

The pretraining method generally uses a large amount of unsupervised data for word vector training. This section introduces an improved pretraining method based on the skip-gram model. The skip-gram model is shown in Figure 6.

As shown in Figure 6, in addition to using words like conventional methods, this paper also uses contextual fea-

tures such as characters, local word order, and part of speech to train word vectors when training the skip-gram model. This not only makes the word vector more detailed but also directly contains part-of-speech information, which will make the model training more convenient in subsequent training.

Inputting words, characters and part-of-speech information into the Skip-gram model and the target are other words around the window. Therefore, in order to make the final result more accurate, this paper will assign a smaller weight to the farther word  $\exp [W_{t+i} W_i]$  in the training sample. Defining the objective function as formula (16),

$$P(W_{t+i}|W_i) = \frac{\exp [W_{t+i} W_i]}{\sum_{m+1}^n \exp [W_{t+i} W_i]}. \quad (16)$$

Although the Skip-gram model avoids the time-consuming increase in the calculation of the hidden layer of the early model, the calculation amount is still very large, especially for large-scale training corpus. In order to speed up the training, this subsection adopts two methods for acceleration.

The negative sampling acceleration strategy selects words that do not exist in the corpus as negative samples  $v_c$  for word strings and calculates to maximize the probability of positive samples. At this time, the positive sample likelihood function is constructed as formula (17):

$$S = \prod_{(w,e) \in D} \sigma(u_w^t v_c). \quad (17)$$

The objective function is defined as formula (18):

$$g = \prod_{(w,e) \in D} \sigma(u_w^t v_c) \prod_{(w,e) \in D} \sigma(-u_w^t v_c). \quad (18)$$

Taking the logarithm to calculate as formula (19):

$$f = \sum_{(w,e) \in D} \log \sigma(u_w^T v_c) + \sum_{(w,e) \in D} \log \sigma(-u_w^T v_c). \quad (19)$$

Deep learning can automatically extract high-level features, avoid a lot of workload in features, and have advantages in dealing with ambiguous words. The internal weights of deep learning include reset weights, update weights, and activate weights [23–25]. When training the forward propagation process, the three internal weights change as in formula (20):

$$\frac{\partial E}{\partial W} = \delta_z, a_t. \quad (20)$$

According to the formula, it can be known that the smaller the total loss  $a_t$ , the more accurate the final result. In order to better distinguish the importance of forward information and backward information, the external weight method is also adopted.

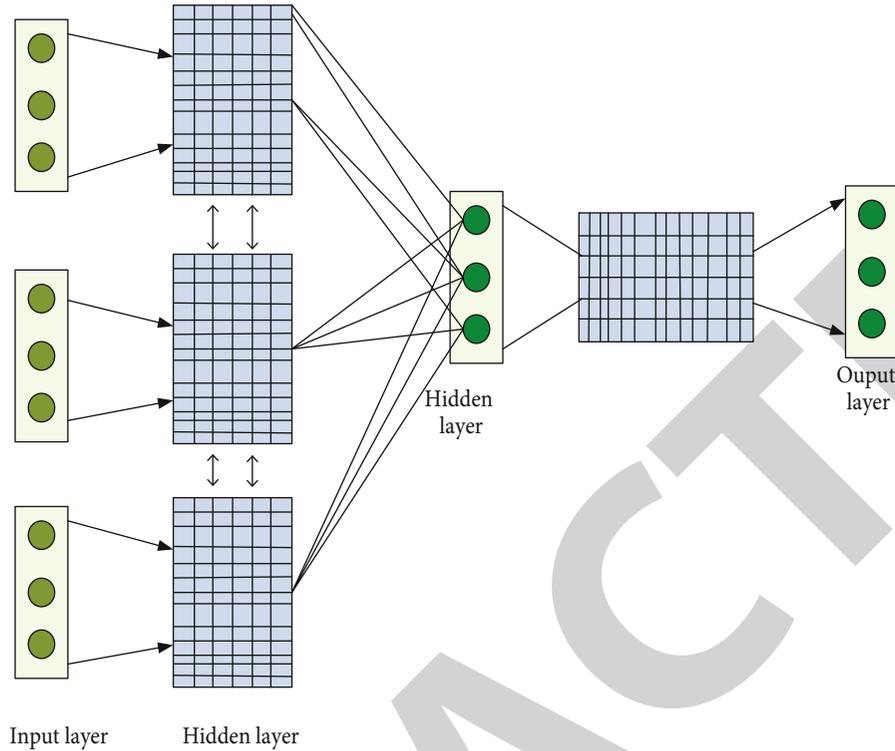


FIGURE 6: Skip-gram model.

## 5. Experiment and Analysis of Traditional Neural Network Algorithm and Pretrained Vector Algorithm

*5.1. Experiments and Analysis of the Shortcomings of Traditional Neural Network Algorithms.* This paper compares the accuracy and processing speed of preposition tagging by traditional neural network algorithm and pretraining vector algorithm, as shown in Figure 7.

As shown in Figure 7, the accuracy of the traditional neural network algorithm for preposition tagging dropped from about 45% to about 20%, while the accuracy of the pre-trained vector algorithm for preposition tagging increased from 2% to about 80%. After the experimental comparison, after using the pretraining vector algorithm, the accuracy and processing speed of spatiotemporal preposition part-of-speech tagging have been significantly improved.

*5.2. Experiment and Analysis of LSTM Model Based on Deep Learning.* Chinese language and literature are an important part of China's excellent traditional culture. In recent years, the number of people studying Chinese literature around the world has increased dramatically, and Chinese language and literature have gradually been paid attention to. Learning Chinese language will help students better understand Chinese traditional culture, not only help students understand the history of Chinese civilization more than 5,000 years through literary works but also improve traditional Chinese culture and the quality of students. Prepositions have the important function of expressing meaning.

This paper compares the shortcomings of traditional recurrent neural networks with the advantages of LSTM based on deep learning, as shown in Figure 8.

As shown in Figure 8, the shortcomings of the traditional recurrent neural network are that the training time is long, the model is too complex, and the characteristics that rely on manual extraction are too high. The advantages of the LSTM model based on deep learning are that the learning efficiency is higher and does not depend on manual extraction.

This paper compares the traditional preposition method and the pretraining algorithm, as shown in Figure 9.

As shown in Figure 9, this paper compares the dependence, error rate, and robustness of the traditional preposition method and the pretraining algorithm. It is found that the traditional preposition method not only has high manual dependence but also has high error rate and poor robustness.

### 5.3. The Importance of Learning Chinese Language and Literature

- (1) With the rapid development of social economy and science and technology, the pace of people's life is also accelerating, and the social atmosphere is becoming weaker and weaker. In this indifferent environment, personal cultivation is especially important if want not to lose oneself. Through continuous research on Chinese and literature, students can truly feel the leap from quantitative change to qualitative change and improve their cultural literacy

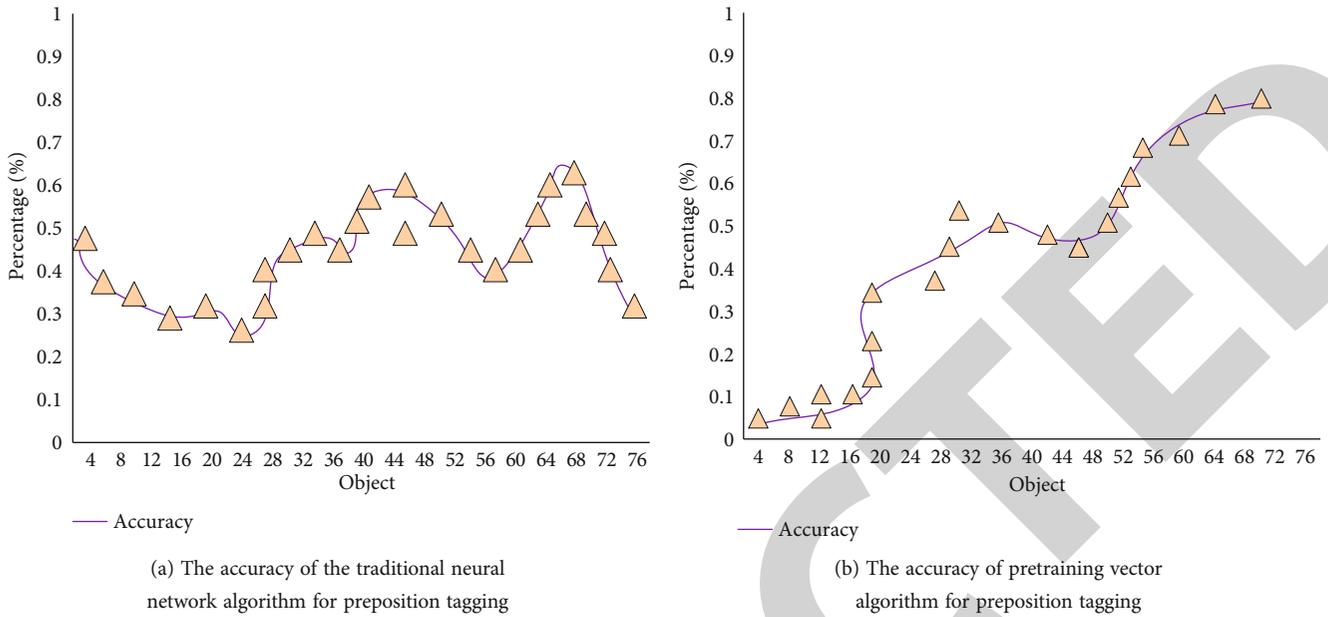


FIGURE 7: The accuracy of preposition tagging by traditional neural network algorithm and pretrained vector algorithm.

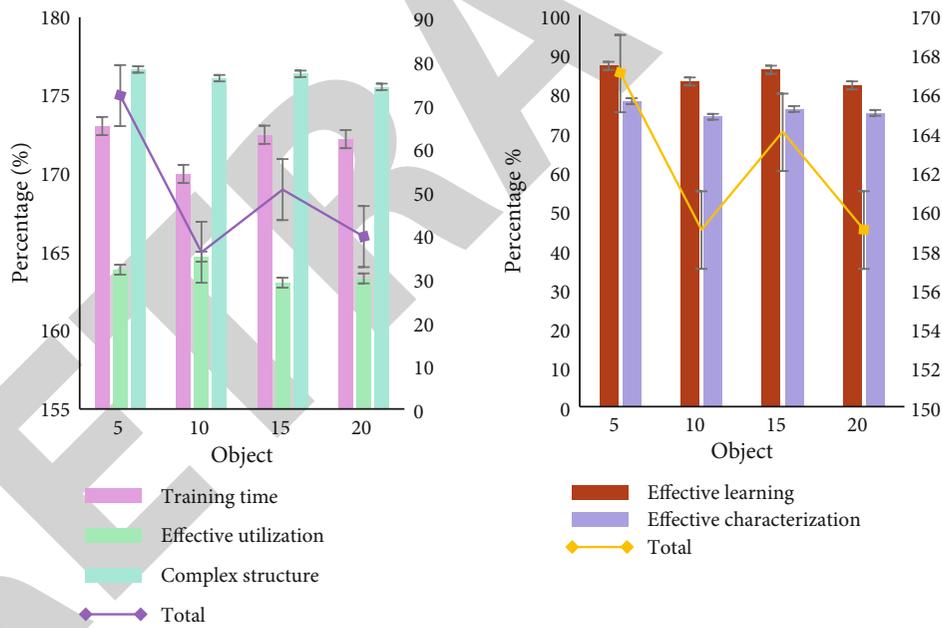


FIGURE 8: Disadvantages of traditional recurrent neural networks and advantages of deep learning-based LSTMs.

(2) Chinese language and literature works are rich in excellent cultural elements and are an indispensable part of excellent Chinese culture. These excellent literary works can play a role in cultural enlightenment, moral planning, and spiritual purification of readers. The heroic characters in literary works have very good personal qualities, and students who study this kind of literary works will be affected invisibly and improve their moral quality and spiritual temperament

(3) It helps to regulate people's behavior. "Harmony is the most important" and "respect for the old and love the young" are traditional Chinese virtues. These virtues cannot be separated from the popularization of Chinese language and Chinese culture. The values and social outlook of "Hundreds of kindness and filial piety first," which have persisted for thousands of years, have also exerted an important influence on modern young people through the Chinese language

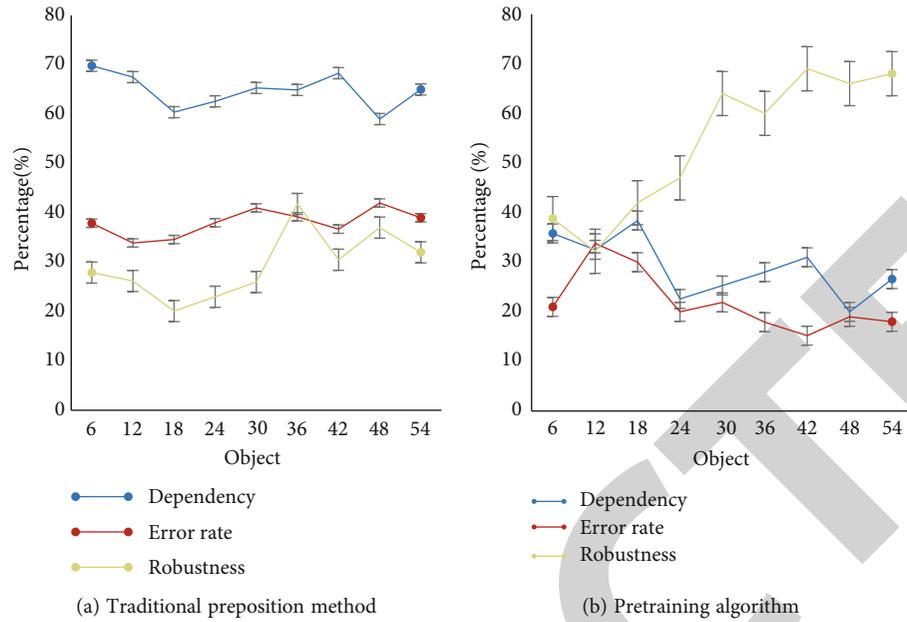


FIGURE 9: Traditional preposition method and pretraining algorithm.

## 6. Discussion

This paper analyzes how to conduct research on spatio-temporal prepositional construction networks based on data analysis and deep learning. This paper expounds the related concepts of deep learning and spatiotemporal prepositions, focuses on the related theories of deep learning, explores the research methods of deep learning on spatio-temporal prepositional construction networks, and discusses the importance of deep learning to spatio-temporal prepositional construction networks through experiments.

This paper also makes reasonable use of artificial neural network algorithm and recurrent neural network model. With the increasing application scope of artificial neural network algorithm and its importance gradually becoming prominent, many scholars have begun to match artificial neural network algorithm with real application scenarios and propose feasible algorithms. The research and analysis of the artificial neural network algorithm actually lays a solid foundation for the research of the combination model of LSTM and linear conditional random field in the experimental part of this paper.

Through the experimental analysis, this paper shows that with the rapid development of the world and the close international communication, China is becoming more and more powerful, and the importance of the Chinese language is getting higher and higher. Therefore, it is necessary to study the spatial-temporal preposition construction network based on deep learning. The combined model of LSTM and linear conditional random field based on deep learning can not only quickly and automatically extract spatiotemporal prepositions but also make the error smaller and smaller.

## 7. Conclusions

Space-time prepositions are the most widely used kind of prepositions, and they show different usage situations in different semantic categories. These situations can be followed by rules and can be explained. And deep learning has the advantage of automatic extraction, which makes it play a huge role in the study of spatiotemporal prepositional construction networks. This paper focuses on the basic concepts of deep learning and spatiotemporal prepositions. In the method part, an intelligent artificial neural network algorithm is proposed based on deep learning. In the experiment, the importance of Chinese language is tested and analyzed, which leads to the importance of spatiotemporal prepositions. The research on the construction network of space-time prepositions is beneficial to the development of Chinese language. Finally, by analyzing the advantages of LSTM and linear conditional random field combined model, it is found that LSTM based on deep learning can not only get rid of the dependence on manual extraction but also reduce errors and greatly improve work efficiency. Although this paper has carried out the experimental analysis of the spatiotemporal prepositional construction network, due to its limited ability, there are still problems of unclear expression in many places.

## Data Availability

No data were used to support this study.

## Conflicts of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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