Retraction

Retracted: Semantic Role Labeling Integrated with Multilevel Linguistic Cues and Bi-LSTM-CRF

Mathematical Problems in Engineering

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] F. Wan, Y. Yang, D. Zhu et al., "Semantic Role Labeling Integrated with Multilevel Linguistic Cues and Bi-LSTM-CRF," *Mathematical Problems in Engineering*, vol. 2022, Article ID 6300530, 8 pages, 2022.

Research Article

Semantic Role Labeling Integrated with Multilevel Linguistic Cues and Bi-LSTM-CRF

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Chinese Semantic Role Labeling (SRL) is the core technology of semantic understanding. In the field of Chinese information processing, where statistical machine learning is still the mainstream, the traditional labeling methods rely heavily on the parsing degree of syntax and semantics of sentences. Therefore, the labeling precision is limited and cannot meet the current needs. This paper adopts the model based on a bidirectional long short-term memory network combined with the Conditional Random Field (Bi-LSTM-CRF). In the feature processing stage, pooling technology is combined with sampling and selecting multifeature vector groups to improve the performance of the sequence labeling model. Lexical, syntactic, and other multilevel linguistic features are integrated into the training to realize in-depth improvement of the original labeling model. Through several groups of experiments, the precision of model annotation in this paper has been significantly improved combined with linguistic-assisted analysis, which proves that it can optimize the annotation performance of the model by integrating relevant linguistic features into the model based on Bi-LSTM-CRF and sampling and extracting multifeature groups; the evaluation of F increases to 82.18 percent.

1. Introduction

In natural language processing (NLP), semantic role labeling (SRL) is one of the important techniques of semantic analysis. The purpose is to label all semantic roles related to predicates in sentences. SRL belongs to shallow semantic analysis. Compared with deep semantic analysis, SRL has the characteristics of simple labeling, clear structure, and easy display. It has a wide range of practical value prospects in many application fields such as question answering (QA) system, information extraction (IE), machine translation (MT), etc. What is more, it can promote the research of deep semantic analysis and text understanding. The main research methods for SRL include CRF, support vector machine (SVM), and other linear machine learning methods; research direction includes named entity recognition (NER), part-of-speech (POS) for SRL, and so on.

According to the existing research on SRL, taking the Bi-LSTM-CRF model as the basic model, this paper studies the improvement method of Chinese SRL, selectively expands the existing basic features, and adds multilevel linguistic features for comparative analysis and the improved precision is demonstrated in experiments.

2. Relevant Research

SRL is a practical scheme in current semantic analysis and processing. With the emergence of statistical machine learning methods in the field of NLP, many large-scale corpus resources with semantic information have been established, which greatly accelerates the practical pace of the development of SRL methods based on feature learning. In the research of English SRL based on machine learning, Prandhan et al. [1, 2] applied the machine learning method of SVM to SRL and achieved good results. Blunsom [3] introduced a more advanced machine learning model-maximum entropy Markov model into this field and achieved better labeling results. Cohn and Blunsom [4]

successfully applied CRF to SRL for the first time. With the rise of artificial intelligence (AI) in the past two years, deep learning methods have been applied to this field. Ronan and Jason [5] applied deep neural networks to frame SRL. This method slows down the manual intervention of traditional machine learning methods to deal with complex features and achieves ideal labeling results. Subsequently, multilayer neural networks of deep learning method also began to be introduced into this field. Socher et al. [6] used the combination of tree structure encoders and neural network units for classification, and Yin and Schutze [7] used a multilayer CNN network model for semantic classification. While these methods have achieved good performance, due to the increase in the number of network layers, the model does not depict linguistic phenomena well. The appearance of the LSTM model can not only effectively solve problems such as gradient disappearance but also consider the dependency relationship between contexts. Therefore, Zhou and Xu [8] used long short-term memory (LSTM) model to label semantic roles and added a small number of lexical features in the model training process, which has good experimental results. Zhen et al. [9] used the Bi-LSTM model, which exceeded the best results known at that time without introducing other resources. Jiang et al. [10] focused on syntactic path information and used Bi-LSTM to model, which improves the performance of the system. At present, the dropout punishment mechanism is widely used.

In Chinese SRL task, the sequence labeling model has made remarkable progress in the application of SRL. In CoNLL 2004, SRL was established as the theme for the first time and was carried out on the basis of shallow syntactic analysis theory. Wang's [11] research on SRL was based on a neural network with an optimized output layer. Although the experimental effect is still far from that of traditional machine learning annotation, this research provided a reference for the application of deep learning algorithm in this field. Therefore, the team tried again to apply the bidirectional cyclic neural network algorithm in 2015. The method avoids a large number of complex feature extraction and can make better use of the information in the annotation sequence. In order to solve the problems of poor information transmission caused by multilayer neural network and gradient explosion caused by too many network layers, Wang et al. [12] proposed setting up a "straight ladder unit" with information connection inside the multilayer LSTM model unit. The labeling information can be quickly transmitted between different layers. Li et al. [13] constructed a lightweight single-layer RNN model by external memory cells. The lightweight model has the advantages of simple training, high labeling efficiency, but its precision is close to that of the multilevel network model. Yang [14] introduced word distribution representation and dropout punishment mechanism into the neural network model, which greatly alleviated the problem of overfitting of the neural network model and significantly improved the labeling performance of the system. Significant progress has also been made in rule-based SRL [15–18]. This study also draws lessons from the model construction methods of relevant works [19–22].

Generally speaking, due to the limited corpus resources of Chinese SRL available for training and because some differences brought by Chinese itself are different from those of English (for example, the target verbs in Chinese are not easy to determine and Chinese SRL need to process word segmentation but English do not; the basic modules of Chinese automatic analysis, such as word segmentation, POS, dependency syntactic analysis [23], and other restrictions, etc.), the development of Chinese SRL is rather tortuous, so there is still much field for improvement in the Chinese SRL.

3. Model Construction

The main idea of the SRL model is to manually mark various semantic roles such as agent, subject, result, and mode in a certain scale corpus. The deep learning method is used for data training from the labeled large-scale corpus, and the probability rules of various semantic roles in different sentences are extracted to estimate and label each semantic role in the new corpus with the greatest probability. For the annotation model, role recognition and role classification are the core steps. Therefore, this paper uses bidirectional long short-term memory (Bi-LSTM) algorithm to solve these problems, and our end-to-end model can obtain features of role recognition and role classification from the embedding layer and further improves the sequence annotation performance of the original model by adding various linguistic features such as lexical and syntax.

3.1. Theoretical Methods. This method adopts the labeling strategy of word sequence labeling and uses a neural network classifier to identify and label various semantic roles in sentences at the same time. In the postprocessing stage, the pooling layer on CNN is used to sample the features and eliminate redundant feature information. After predicting all the matching semantic roles, simple postprocessing rules are adopted to identify the semantic role components that cannot be matched, and the semantic role with the highest prediction probability is retained.

In the selection of the annotation model, this paper mainly considers the current mainstream sequence annotation model based on deep learning: Bi-LSTM model. LSTM is an improved model based on the recurrent neural network (RNN) which has a strong nonlinear fitting ability. During model training, examples are mapped through complex nonlinear transformations in high-order and high-latitude heterogeneous spaces to obtain a low-dimensional sequence model. Compared with the traditional machine learning model, there is no flexibility to add custom features. When the semantic roles in a complex corpus are not completely separable, the labeling performance is poor, and the relevant information between elements in the sequence cannot be fully considered. Due to the design characteristics of LSTM, it can greatly improve the shortcomings of traditional machine learning methods and better take into account the sequence relationship of elements before and after the sequence, which is very suitable for modeling

complex nonlinear sequence data, such as text data. Therefore, the Bi-LSTM model would be adopted for achieving greater improvement in labeling performance.

3.2. Labeling Model.
We use Bi-LSTM-CRF model for SRL task. Bi-LSTM is an improved model based on recurrent neural network (RNN), which consists of forward LSTM and backward LSTM. Due to the design characteristics, the model has a super nonlinear fitting ability and can realize automatic feature extraction and bidirectional encoding of context information, which can solve the long-distance dependence in sentences and is very suitable for processing time-series data, such as text data. However, the results obtained by Bi-LSTM contain a lot of useless information. After Bi-LSTM, the label transition probability matrix is introduced as a constraint condition, and CRF is used to fuse the global label information to obtain the optimal label sequence, which can improve the performance of the model. In this model, average pooling in CNN is used to sample the input features of the word embedding layer in the data preprocessing stage. The purpose is to sample and extract multifeature groups, eliminate redundant features, and complete word vector adjustment. This model is mainly composed of an input layer, word vector layer, average pooling layer, Bi-LSTM layer, and CRF layer architecture. The main architecture of the model is shown in Figure 1.

3.2.1. Pretreatment Layer.
The model sends a sequence after the input layer; each word in the sequence is mapped into a corresponding word vector through the preprocessing layer and sent to the Bi-LSTM layer. Assuming that the input sentence A contains n word, $A = \{x_1, x_2, \ldots, x_n\}$, x_i represents the i word in the input sentence. The word vector matrix E_w is used to obtain the word vector. v^w represents the vocabulary size. By (1), a word x_i can be converted into a word vector e_i:

$$e_i = E_w v^i, \tag{1}$$

where v^i is the absolute value distance of the vector v^i. After the above preprocessing, the initial sequence fragment sentences will enter the Bi-LSTM layer network in the form of word vectors.

3.2.2. Bi-LSTM Layer.
The basic idea of the Bi-LSTM layer is to synchronously add a training sentence to forward and backward cyclic RNN and the units trained by the two RNNs points to a Max pooling layer interface at the same time. This two-way structure can provide a max-pooling layer with sufficient context-related information for each word in the input sentence. The network framework of its LSTM layer is shown in Figure 2.

Among them, the current input word corresponding to the time sequence t is X_t, the cell state is C_t, and the hidden layer state is h_t. The training process can be understood as processing the new element information in the current time sequence state through forgetting and memory units, retaining and transmitting the information with larger

influence factors to the cells in the next time sequence state, filtering the information with smaller influence factors, and outputting the hidden layer state h_t in the time sequence state. After iteration, in turn, the hidden layer timing state $\{h_\Omega, h_1, \ldots, h_{n-1}\}$ corresponding to the sentence sequence can be obtained. "AretanA" is function of arctangent.

Bi-LSTM is a two-way combination of the forward pass and backward pass, which takes into account the common context information in semantic role annotation tasks. The hidden layer state of the i word is shown as follows:

$$h_i = \overrightarrow{h_i} \oplus \overleftarrow{h_i}. \tag{2}$$

3.2.3. Posttreatment Layer.
In the process of SRL, the location information of features inside the sentence sequence is very important. For example, the agent is generally located at the beginning of the sentence, the subject is located at the end of the sentence, and the core component is between them. The location information of these features is very important for role recognition and classification. However, the advantages of max-pooling technology are as follows. (1) The positions of the main features in the annotation sequence can still keep the feature position information and rotation unchanged after model training. (2) It can be used to reduce network parameters, model complexity, and iteration times in neural network model training. (3) When the features are pooled, the number of parameters of each filter and the number of neurons corresponding to fixed feature vectors can be significantly reduced. Therefore, this model introduces Max pooling technology in the post-processing layer.

3.2.4. CRF Layer.
In SRL, there is a strong connection between the labels of adjacent words. For example, in the labeling system in this paper (Table 1), the label I_ARG0 can only be B_ARG0 or I_ARG0 before, while the label B_ARG0 can only be I_ARG0, O, or B_X after, and the rest of the labels are illegal. It is unreasonable to directly select the label with the highest score corresponding to each word output by the Bi-LSTM layer as the optimal label. The CRF layer introduces the label transition probability matrix, which can learn the label constraints of adjacent words from the training data and improve the performance of the label model. In addition, this paper adopts the Viterbi algorithm to infer the optimal label sequence.

4. Experiments

At present, the LSTM model has achieved good results in text information processing tasks of sequence labeling. This method not only overcomes the conflict between the sentence vector representation and the original sentence semantics caused by the original convolution neural network model, not considering the word order relationship in the sentence sequence, but also significantly improves the memory ability of the initial part of elements in long sentence patterns.
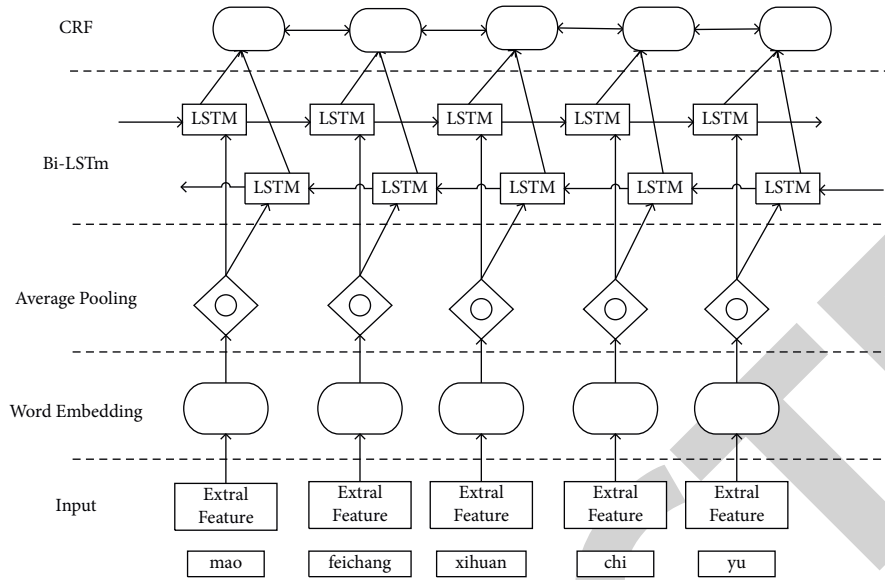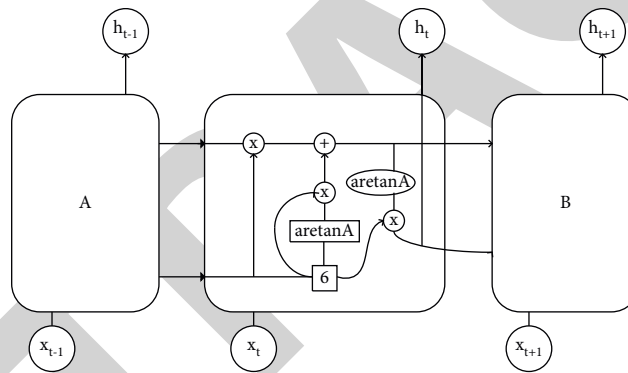
Figure 1: Model architecture of SRL.

Figure 2: Network framework at the LSTM layer.

Table 1: Comparison of annotation results of whether CRF is added or not.

Sentence	Qunain	Shixian	Jinchukou	Zongzhi	a	1,090	Meiyuan
Correct label	B-ARG0	I-ARG0	I-ARG0	I-ARG0	el	B-ARG1	I-ARG1
Forecast label without CRF	ARGM-LOC	I-ARG0	I-ARG0	I-ARG0	el	B-ARG1	I-ARG1
Forecast label add CRF	B-ARG0	I-ARG0	I-ARG0	I-ARG0	el	B-ARG1	I-ARG1

This paper uses public CPB corpus for experiments and Bi-LSTM-CRF for training. Based on this initial model, several groups of new features are added to the corpus, average pooling is integrated to sample and select the formed feature vectors, and the basic model is gradually optimized and trained. Finally, the model is evaluated, and relevant experimental conclusions are obtained through analysis and comparison.

4.1. Corpus Selection. In terms of Chinese SRL corpus, due to the lack of large-scale training corpus in different fields, there is no good breakthrough in various types of SRL methods in domain adaptation. Therefore, we only consider the labeling problem in a single field. In the experiment, the SRL system adopted Chinese PropBank (CPB). This system divides the semantic roles into two categories (Table 2). (1) The core semantic roles ARG0 ~ ARG5. ARG0 denotes the agent of the action, ARG1 denotes the subject of the action, and ARG2 ~ ARG5 have different semantic meanings according to different predicates. (2) Additional semantic roles. 13 subtypes such as location, reason, time, etc., are marked as ARG-X. For example, the location is marked as ARGM-LOC.

The corpus constructed in this experiment uses CPB partial data sets with a comprehensive semantic description and moderate granularity. After screening and statistics, there are 18,000 sentences in the training set, 1200 sentences in the development set, and 2,000 sentences in the test set.

Table 2: Format of basic training corpus.

Sentence	Zhongguo	Youse	Jinshu	Hangye	Baochi	Shiwu	Nian	Chixu	Zengzhang
Labeling	ARG-1	ARG-1	ARG-1	ARG-1	Rel	ARG-2	ARG-2	ARG-2	ARG-2

There are 18,418 words in the statistics. The first 13,000 words are selected as the vocabulary, and all words not included are replaced by_UNK. Table 2 shows the labeling schema.

In addition, this paper adopts precision, recall, and F1 values as evaluation indexes of argument recognition performance in SRL. The evaluation index equation in this paper is as follows, P is expressed as precision, R is expressed as recall, and F1 is equal to $2 * P * R/(P + R)$:

$$P = \frac{T}{W},$$
$$R = \frac{T}{V}. \tag{3}$$

T is the number of proposition arguments correctly recognized by the system, W is the number of all proposition arguments recognized by the system, and V is the number of all proposition arguments in the standard mark.

4.2. Model Parameters.
Bi-LSTM model is used to extract the feature attributes of sentence sequences, and the hidden layer of Bi-LSTM is output and pooled to the maximum extent to obtain all possible labeling results Y^*. Y^* is input into the discrimination function of the postprocessing layer, and the labeling result Y with the maximum probability is output after discrimination. The experimental flow of the labeling model is shown in Figure 3.

The model hyperparameters are shown in Table 3. The model is trained using the hyperparameter settings in Table 3.

4.3. Experimental Comparison.
Chinese sentences include many linguistic cues, for example, POS, dependency syntax, and sentence framework; we consider these features can do help for our model. So experiments below are also based on these features.

Experiment 1: on the basis of the Bi-LSTM-CRF model, test and compare the performance improvement effect of integrating POS and argument into the basic corpus. The test results are shown in Table 4.

Analyzing the test results and comparing the evaluation of the precision, recall, and F1 value of the two models, it is shown that the performance of the model integrated with lexical features is generally better than that of the model trained with the basic corpus.

Experiment 2: on the basis of adding two groups of features such as POS in Experiment 1, dependency syntactic features are added to the training corpus. That is, the distance from the current word to the predicate and the dependency relationship are added to the training corpus. The test compares the performance improvement effect of integrating dependent syntactic features (the details of
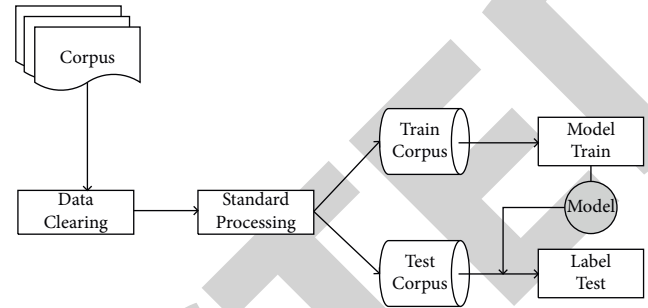

Figure 3: Experimental flow chart based on the Bi-LSTM model.

Table 3: Hyperparameter setting table.

Hyperparameter	Settings
Word vector dimension	150
Each feature vector dimension	15
Hidden layer dimension	128
Dropout	0.5
Learning rate	0.001

Table 4: Comparison of labeling results incorporating POS features.

	Precision (%)	Recall (%)	F1 (%)
Incorporate new feature groups	78.09	74.28	77.74
Control group	78.39	74.03	77.30

dependent syntactic features are added to the table, the sentence threshold discrimination table, and the labeling number is wrong) into the corpus of Experiment 1, and the results are shown in Table 5.

Analysis of the results in Table 4 shows that the model that integrates dependency features on the basis of adding part-of-speech features greatly improves the labeling performance, which is better than the model that only adds two groups of features such as part-of-speech.

Experiment 3: based on the analysis of Experiment 2, it is found that there is a big gap in the prediction results of sentences of different lengths. Among them, the labeling error rate of core components in long sentences is higher, while the labeling error rate of non-core components in short sentences is higher. Therefore, the experiment assumes to add sentence pattern discrimination features to the first three groups of feature corpus to explore whether to further improve the performance of the model. The discrimination method is to add a column of sentence pattern discrimination features to the corpus, and the threshold setting of sentence pattern features is shown in Table 6.

According to statistics, various sentence patterns in the corpus are shown in Figure 4. It can be seen that super-long

Table 5: Comparison of annotation results incorporating dependency features.

	Precision (%)	Recall (%)	F1 (%)
Incorporate new feature groups	80.83	75.30	78.44
Control group	78.09	74.29	77.74

Table 6: Sentence threshold discrimination.

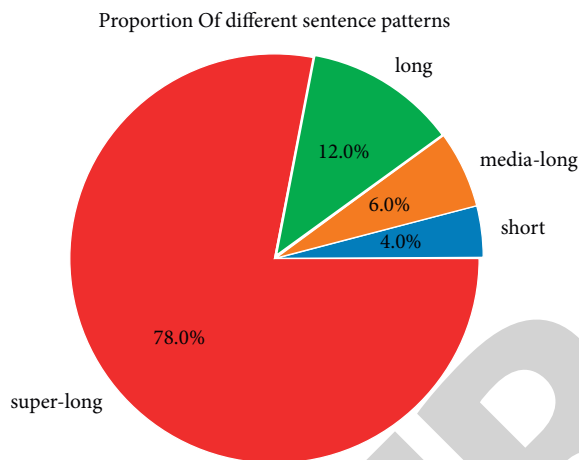| Sentence type	Number of elements/X
Short sentence	$X \leq 10$
Middle sentence	$X \leq 15$
Long sentence	$X \leq 20$
Super-long sentence	$X > 20$

Figure 4: Proportion of different sentence patterns.

sentences account for the vast majority of the training corpus, followed by long sentences and short sentences.

After comparative tests, the results are shown in Table 7.

The analysis of the experimental results shows that the labeling precision of the non-core components of short sentences and the core components of long sentences with similar semantics and consistent sentence patterns in the training corpus has been improved to a certain extent.

Experiment 4: through the above experiments, it is found that integrating part-of-speech features, dependency features, and sentence features into the basic corpus can improve the performance of the model. However, with the increase of integrated features, the performance improvement effect of the model slows down. Therefore, the experiment assumes further feature extraction and sampling to explore whether the performance improvement effect brought by multilevel cue features to the model can be better released. The experimental test results are shown in Table 8.

The corpus used in this experiment is a multifeature training corpus that integrates POS, whether it belongs to arguments, dependent syntactic features, and sentence patterns. The above two models are trained and tested, respectively. Through the analysis of Table 8, it can be seen that the Bi-LSTM-CRF model integrated with the average pooling method is superior to the Bi-LSTM-CRF model

Table 7: Comparison of labeling results incorporating sentence pattern features.

	Precision (%)	Recall (%)	F1 (%)
Incorporate feature set	81.44	75.17	78.98
Control group	80.83	75.30	78.44

Table 8: Comparison of annotation results of two models.

	Precision (%)	Recall (%)	F1 (%)
Bi-LSTM-CRF + pooling	82.18	76.52	79.41
Bi-LSTM-CRF	81.44	75.17	78.69

without feature extraction and sampling in three evaluation indexes.

The comparison between the previous SRL results and the experimental results finally obtained in this paper is shown in Table 9.

4.4. Experimental Analysis. This experiment is an improvement attempt to the deep learning Chinese SRL model. The constructed corpus contains not only a large number of sentences with verbal predicates but also a large number of sentences with nominal predicates, which is close to the real language environment. Experiments show that different kinds of CNN models have a great influence on the annotation precision, and it is very important to select the appropriate annotation model. The Bi-LSTM model with Max pooling technology not only overcomes the conflict between the sentence vector representation and the original sentence semantics caused by the traditional CNN model not only considering the word order relationship in the sentence sequence but also significantly improves the memory ability of the initial part of elements in long sentence patterns. In order to verify the hypothesis of a correlation between different part-of-speech granularity and labeling precision, three groups of control experiments of coarse particle size, fine particle size, and coarse-fine particle size were carried out. The experimental results show that different particle size of a POS has a certain influence on the labeling precision, and the fine particle size training model has better labeling results than the coarse particle size training model. However, when the coarse and fine particle size training model is tried to combine, the labeling performance of the model does not increase but decreases. Compared with the training logs of the model, it is found that, with the complexity of POS granularity, the number of semantic role labels increases exponentially. The increase in the number of labels will be directly reflected in the increase in the number of features, while the excessive number of features will lead to the deterioration of the convergence speed of the model. The analysis of test results shows the following. (1) A large number of redundant or irrelevant features appear in the training model generation process. (2) Due to the difference in the size and granularity of POS, the model has different meanings when labeling named entities such as person names and organization names. For linear sequence classification annotation, the more detailed the

TABLE 9: Comparison of final experimental results with previous results.

Experimental team	Precision (%)	Models
Literature [3]	79.25	Maximum entropy Markov
Literature [8]	81.07	End-to-end
Ours	82.18	Bi-LSTM-CRF

features, the better the model performs. Too many features will easily lead to information redundancy, increase the system burden, and drag down the overall annotation precision of the model. The error analysis of the labeling results shows that, under the condition of similar sentence patterns, the error rate of non-core components in short sentences and core components in long sentences is relatively high, and it is conjectured that the labeling precision of sentence patterns and similar semantic sequences can be improved by adding long and short sentence labels. Experiment 3 verified this conjecture. By adding sentence pattern threshold features, the labeling precision of the model for the parts with a higher error rate of long and short sentences has been improved to different degrees.

Experiments show that each new feature will have different degrees of influence on the experimental results. In addition, when the model makes an annotated prediction, it may produce some unexpected prediction results (such as multiple core components, transcending boundaries, depending on edge crossing). It is the focus of our next task to solve these problems.

5. Conclusion and Next Work

Semantic roles are widely used because of their conciseness, clarity, and easy labeling. SRL, as a research key point connecting syntax and semantic layer, has high research value in NPL applications. In the construction of Chinese SRL model based on Bi-LSTM-CRF, this paper attempts to integrate multilevel linguistic features into the training corpus. During model training, use average pooling to sample and extract multifeature vector groups in the word vector processing stage; with these processes, the model can reduce the training difficulty and better release the potential of multicue features. The experimental results show that, by adding new features, it is confirmed that the annotation performance of the model can be improved to a certain extent. In addition, in the feature vector processing stage, average pooling integrated with CNN can further improve the labeling precision. In the future research work, we will focus on integrating high-order features that can embody structure into the model, making detailed role discrimination rules, and introducing semantic similarity calculation, so that the model can identify semantic role targets faster and more accurately. Next, we will add phrase syntactic features to our model and try to find some influence and achieve some improvement or not.

Data Availability

The data used to support the findings of this study are included within the article.

Disclosure

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Fucheng Wan contributed to design of paper ideas and paper writing. Yimin Yang sorted out the current situation of research at home and abroad. Dengyun Zhu contributed to the extraction of linguistic features and the study of linguistic ontology. Hongzhi Yu ∗ participated in paper writing and experimental methods. Ao Zhu contributed to construction of the underlying model of SRL. Guoyi Che carried out experiments test and analysis. Ning Ma contributed to revision of the paper and format adjustment.

Acknowledgments

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