Geographic entity relationship extraction model based on improved CasRel

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ABSTRACT

Geographic entity relationship extraction is a vital task in the field of Geographic Information Science (GIS) and Natural Language Processing (NLP) that aims to extract relationships between geographic entities from text. The current field of geographic entity relationship extraction lacks a public corpus and the existing models face limitations in addressing long-distance relationship modeling and relationship diversity. Therefore, in this study, we first construct the GeoRelCorpus, a corpus encompassing a wide range of geographic entities and relationships. It is based on the Encyclopedia of China Geography branch, and supplemented with the tagging information of OpenStreetMap. The primary objective is to facilitate the training and evaluation of geographic entity relationship extraction models. In terms of model design, we propose an enhanced CasRel model that integrates a multi-scale feature extraction module, combining IDCNN, BiLSTM, and SENet components to improve feature extraction capability and extraction accuracy. Finally, experiments are conducted on the Baidu entity-relationship extraction dataset and GeoRelCorpus. The results demonstrate a notable enhancement in the F1 value achieved by our improved model, thus confirming its effectiveness.

Keywords: Entity relationship extraction, improved CasRel, geographic entity relationships, GeoRelCorpus

1. INTRODUCTION

The rapid development of natural language processing enables computers to understand and process textual information, and entity-relationship extraction, as a key part of it, has attracted increasing attention from researchers[1]. The goal of entity-relationship extraction is to identify entities from text and infer the relationships between them, the key is to deeply understand the semantic information in the text, to identify entities representing specific concepts in the text, and to understand the semantic associations between them. This lays the foundation for tasks such as deepening text understanding, building knowledge graphs[2], information retrieval, and intelligent Q&A[3].

In the field of geographic information science, geographic entity relationship extraction is a special application of entity relationship extraction. Its task is to extract geographic entities, such as place names and regions, from geospatial texts and to reveal the spatial relationships among them. This is of great practical significance for the in-depth understanding of geographic phenomena, the construction of geographic knowledge maps, and supporting the development of geographic information science.

In entity-relationship extraction methods, the traditional pipelined extraction method first performs entity identification and then relationship classification[4]. However, this method is prone to error propagation and information loss[5]. In specific domains, such as geographic information science, there are higher requirements for the accuracy and efficiency of geographic entity relationship extraction. Relationships between geographic entities are more diverse, i.e., they include geographical location, terrain features, administrative divisions, population, area, etc., reflecting the complexity and diversity of geographical space, and embodying various Interconnections and interactions between geographical elements. At the same time, a large part of these relationships are long-distance relationships. Long-Distance Relationship Modeling refers to the relationship between entities that exist over a long distance in the text. These entities may not be directly adjacent in the text, or may even be separated by multiple sentences or paragraphs. Long-distance relationship modeling often involves information extraction and association across sentences or paragraphs.

In this case, traditional local context-based methods may not be effective enough because the information about entities and relationships is scattered in different parts of the text. Therefore, long-distance relationship modeling requires the use

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of more complex models to capture contextual information between entities[6]; In recent years, joint model extraction methods have gradually gained attention to simultaneously extract entities and relations through a single model to improve the consistency and accuracy of the extraction[7]. CasRel[8] as a joint extraction model has achieved good results in the relation extraction task, but it simply inputs the individual word vectors into the classifier during the annotation process, ignoring the contextual information of the entities, which leads to a limitation in solving the long-distance relation modeling limitations. For this reason, this paper incorporates a multi-scale feature extraction module for the CasRel model to enhance the feature extraction capability of the model and improve the model's ability to model long-distance relationships. In addition, to address the scarcity of large-scale annotated data on geographic entity relationships[9,10], this paper constructs a corpus of diverse geographic entity relationships based on the Encyclopaedia of China Geography Subsection. Through experiments, we demonstrate that our approach achieves significant performance improvement on both the public relationship extraction dataset and the self-constructed geographic entity-relationship extraction dataset GeoRelCorpus, which provides an innovative solution for the entity-relationship extraction task in geographic information science.

2. RELATED WORK

Geographic entity relationship extraction, as a key task in the field of geographic information science, aims to the extraction of geographic entities and their relationships from text. With the continuous development of deep learning technology, deep learning-based methods have gradually become mainstream. Traditional entity-relationship extraction methods usually adopt a pipeline approach, where the entity-relationship extraction task is decomposed into two independent steps of entity recognition and relationship extraction, with entity extraction followed by relationship classification[11]. The main methods used are RNN and CNN and their improved models.

Socher et al.[12] introduced an RNN model into a relational extraction task to overcome the limitations of the word vector model in understanding the meaning of the components of longer phrases. Lin et al.[13] overcame the constraints of the neural network model on limited labeled instances by constructing a recurrent neural network with multi-semantic heterogeneous embeddings. Wang et al.[14] proposed a convolutional neural network architecture to support end-to-end learning with two-stage attention to better recognize relational patterns in heterogeneous environments. Wang et al.[15] proposed a lightweight relational extraction method to drive convolutional neural learning with structural blocks.

This approach clarifies the task flow, making the modeling of each step relatively simple to understand and adapt. However, its inherent shortcomings include error accumulation[16], information segregation due to independent execution of tasks[17], long dependencies that are difficult to handle, possible information redundancy, and an overall lack of global optimization[4].

In recent years, to improve the consistency and accuracy of entity-relationship extraction, researchers have gradually turned to joint entity-relationship extraction methods, trying to accomplish both entity and relationship extraction in one model. Katiyar[18] proposed an attention-based recurrent neural network for joint entity extraction and relationship extraction. Zheng et al.[19] proposed a hybrid neural network model for entity and relationship extraction tasks. Bekoulis[16] proposed a joint neural model for performing both entity recognition and relation extraction without the need for manual feature extraction or external tools. Zheng et al.[20] proposed a new labeling scheme to convert the joint extraction task into a labeling problem. Wei et al.[8] proposed a novel cascading binary tagging framework (CasRel) modeling relations as functions that map subjects in sentences to objects, effectively solving the overlap problem.

For the geographic domain, several types of research have been devoted to the accurate extraction of geographic entity relationships through rule-based pattern matching, machine learning, and other methods. Du et al.[21] constructed a spatial query language integrating detailed, exterior, and topological relations for spatial data retrieval. Chen et al.[22] analyzed regularized natural language positions, proposing structured expressions and an estimation method. Zhang et al.[23] and Du et al.[24] used SVM and Random Forest models for spatial relation extraction, achieving recognition and classification of spatial expressions. Yu et al.[25] extracted entity relations from contextual keywords using lexical, positional, and distance features with a machine learning approach.

In geographic entity relationship extraction, the rule-based pattern-matching approach suffers from rigidity constraints, difficulty in maintenance and updating, insufficient generalization capability, difficulty in dealing with diversity, and an inability to resolve semantic ambiguities. And it is greatly dependent on the rule set. Machine learning-based approaches rely on a large amount of labeled data, need to manually design features, and are difficult to deal with complex contexts and long-distance dependencies. Therefore, in this paper, we constructed a corpus of geographic entity relationship extraction through manual labeling; integrated the multi-scale feature extraction module in the CasRel model, through the combination of IDCNN and BiLSTM, and fused the SENet channel attention mechanism to make the model better capture semantic information, enhance the model's ability to understand multi-level and multi-scale information, and improve the performance of geographic entity relationship extraction. This helps the model to capture entity relationships in text more comprehensively and accurately. These works provide useful insights and methods for solving key problems in geographic information science.

3. IMPROVING THE CASREL ENTITY-RELATIONSHIP EXTRACTION MODEL

3.1 GeoRelCorpus construction for geographic entity relationship extraction Corpus

The construction of the corpus GeoRelCorpus in this paper is based on the Encyclopedia of China: China Geography (ECCG) and combines the tag information (from taginfo) of OpenStreetMap (OSM) to define the categories of geographic entities.

(a) Data preprocessing: The Encyclopedia of China: China Geography (ECCG), as an authoritative geographical knowledge reference, can ensure the reliability of the data. Secondly, we performed data cleaning and preprocessing and adopted strict standards and specifications to ensure the annotation and labeling of the corpus. The format complies with best practice standards, removing text related to non-geographic entities and retaining semantic and spatial information related to geographic entities; then, in order to ensure the diversity of data, the corpus covers different regions and different types of geographic elements; finally, we Repeated proofreading work was carried out to ensure that the text and labels in the corpus were accurate.

(b) Definition of Geographic Entity Categories: Based on the label information provided by OSM, different geographic entity categories are defined considering different attributes of geographic entities, which are roughly categorized into three types (1) administrative divisions: including districts/counties, cities, provinces, countries, etc.; (2) physical geography: mountain ranges, rivers, lakes, oceans, plains, deserts, plateaus, etc.; and (3) transportation facilities: highways, railroads, airports, ports, and train stations.

(c) Relationship categories: Define the categories of relationships between geographic entities, which are divided into two categories according to whether the relationship types can be described qualitatively: (1) Qualitatively described relationships: topological relationships include neighboring, crossing, overlapping, etc., which are used to describe the spatial relative positional relationship between two geographic entities and the way of connectivity between them; orientation relationships include east, south, west, north, southeast, northeast, southwest, northwest, which are used to describe the relative orientation relationship between two geographic entities; species relationship including located in, belonging to, containing, alias, etc., used to describe the hierarchical structure between two geographic entities, regional division and other conceptual relationships. (2) Quantitative description of the relationship: distance relationship is used to describe the specific distance between two geographic entities, often with a specific unit of measurement, such as kilometers, meters, etc.; attribute relationship is used to describe a variety of characteristics of geographic entities, including the area, elevation, depth, population and so on.

GeoRelCorpus contains 74,797 labeled texts, which are divided into training, testing and validation sets according to the ratio of 7:1.5:1.5. GeoRelCorpus contains 74,797 tagged texts, which are divided into training set, test set and validation set according to the ratio of 7:1.5:1.5. The dataset includes 160,345 annotated entities for administrative divisions, 187,409 for physical geography, and 79,746 for transportation facilities, alongside 44,904 annotations for topological relationships, 52,472 for orientation, 48,654 for species, 5,195 for distance, and 16,304 for attributes. In this paper, a total of 35 entity categories and 30 relationship categories are defined. Referring to the text of the Encyclopedia of China Geography, these 35 entity category annotations are a further subdivision of the three categories of entities. Physical geography, administrative divisions, and transportation facilities are not used as labels but are used to summarize the overall entity category composition. The 35 geographical entities do not include other non-geographic entity types, such as the number of people, area size (square kilometers), distance (meters, kilometers), altitude (meters), etc. The extended-SPO (Subject-Subject Categories-Predicate-Object-Object Categories) annotation is adopted according to the defined entity, entity categories, and relationship types, forming the entity-relationship quintuple. Examples of the specific labeling of the dataset are shown in Table 1. For <“The Ailao Mountain”, “Mountains”, “Start from”, “the south of Dali Prefecture”, “Region”>, “Start from” denotes the relationship category, “Mountains” and “Region” respectively denote the entity categories of subject and object, and “The Ailao Mountain” and “the south of Dali Prefecture” are the names of the subject and object respectively. Training and evaluating the performance of the model on the long text dataset provides a more effective measure of the model's ability to model long-distance relationships and handle relationship diversity.

Table 1. Example of GeoRelCorpus dataset annotation.

Text	Triples
The Ailao Mountains are the demarcation line between the Yunnan Plateau and the Hengduan Mountains and a natural barrier to the climate of the Yunnan Plateau. It is the southern branch of the Yunling Mountains, starting from the south of Dali Prefecture and ending in the south of Honghe Prefecture, with a length of 1000 kilometers. It is mainly composed of sand shale, limestone, and various kinds of metamorphic rocks. The eastern part of the mountain is steeper and has a large relative height difference due to the downcutting along the fault zone, while the western slope is more gentle.	<“The Ailao Mountain”, “Mountains”, “Start from”, “the south of Dali Prefecture”, “Region”> <“The Ailao Mountain”, “Mountains”, “End in”, “the south of Honghe Prefecture”, “Region”> <“The Ailao Mountain”, “mountains”, “Length”, “1000”, “kilometers”> <“The Ailao Mountain”, “Mountains”, “Geological features”, “sand shale, limestone and various kinds of metamorphic rocks”, “Rock type”> <“The Ailao Mountain”, “Topographic features”, “Mountains”, “The eastern part of the mountain is steeper”, “Terrain”> <“The Ailao Mountain”, “Mountains”, “Terrain features”, “large relative height difference”, “Terrain”>

3.2 Model structure

The CasRel model proposed in the literature is an entity relationship extraction model based on cascade decoding, and its structure mainly includes an encoding part and a decoding part, in the encoding part, the contextual information obtained only based on the BERT encoding layer, which therefore leads to the insufficient representation of contextual information. In this paper, the encoding part is improved by adding a multi-scale feature extraction module (IDCNN + SENet + BiLSTM) in order to enhance the model's ability to represent contextual information and model complex relationships. The overall framework of the model is shown in Figure 1.

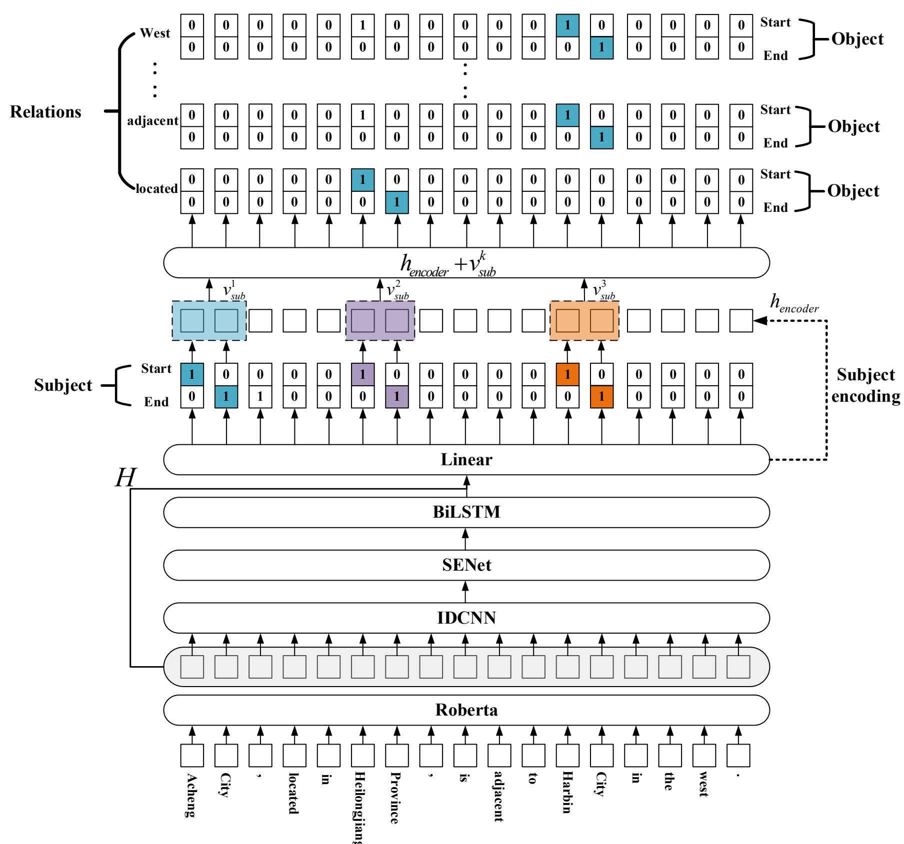

Figure 1. GeoRelCorpus construction process.

3.2.1 Encoding part. (1) Roberta encoding: the input text is encoded using the pre-trained language model Roberta to obtain the contextual semantic representation of each word/phrase. Let the model input text sequence $X=(x_1,x_2,x_3,\ldots,x_t)$, then the output $H=(h_1,h_2,h_3,\ldots,h_t)$ after encoded by Roberta model can be expressed as:

$$H=Roberta(X) \tag{1}$$

where $t\in[1,n]$, n is the sentence length.

(2) Multi-scale feature extraction module (IDCNN + SENet + BiLSTM): the IDCNN in the module can capture information at different scales by dilated CNN, increasing receptive Field of the convolution kernel. This allows the model to understand the semantic information in the text more comprehensively. First, Roberta's encoding output H is fed into the IDCNN model, which is composed of four dilated CNN blocks with the same structure put together, and inside each block, there are four dilated CNN layers with a dilation width of 1, 1, 2, 4, respectively, then the output of the IDCNN:

$$H_{dilated}=LN(DilatedCNNBlock(P(W\times H+b))) \tag{2}$$

where W is the weight matrix, b is the bias term; P denotes the dimension substitution, LN denotes the normalization operation, and $DilatedCNNBlock$ denotes the dilation convolution operation, for input H, the dilation convolution is implemented as follows:

$$c_t^{(1)}=D_1^{(0)}h_t \tag{3}$$

$$c_t^{(j)}=R(D_{2^t}^{(j-1)}c_t^{(j-1)}) \tag{4}$$

$$c_t^{(n+1)}=R(D_1^{(n)}c_t^{(n)}) \tag{5}$$

where $D_\delta^{(j)}$ is the dilated convolutional neural network with the dilated distance of δ in the j-th layer; $c_t^{(j)}$ is the feature received by the j -th (j >1), convolutional layer; $R()$ denotes the ReLU activation function.

The SENet (Squeeze-and-Excitation Networks) channel attention mechanism allows the model to adaptively learn the weights of each channel, which enables the model to adjust its attention to different channels during the training process, helps the model to focus its attention on specific channels that are important to the task, and enhances the model's expressive ability, thus improving the model's performance. At the same time, SENet introduces relatively few parameters and does not significantly increase the computational complexity of the model. Taking the output of IDCNN as the input of SENet, the output of SENet can be expressed by the following formula:

$$O_{se}=\sigma(W_e\times f_{pool}(H_{idcnn}))\odot H_{idcnn} \tag{6}$$

The global information representation is obtained by pooling the entire sequence H_{idcnn} through the global pooling function f_{pool}. The global representation is then modeled by a linear transformation W_e and an activation function σ to obtain the attention weights. Finally, this attention weight and the original sequence are multiplied element-by-element $\odot$ to obtain the final output O_{se}.

BiLSTM further extracts the correlation features between entities and removes the noise information through its gating mechanisms, while modeling the temporal relationship of sequences to better understand the semantics and structure in the text. The output of SENet O_{se} is fed into the BiLSTM model, and learning of features from O_{se} above and below to obtain $\overleftarrow{O}_t$ and $\vec{O}_t$, respectively, and then the output of the BiLSTM model is $O=(o_1,o_2,o_3,\ldots,o_t)$. where $O_t=\overleftarrow{O}_t+\vec{O}_t$ denotes the output of the BiLSTM unit at the moment t .

3.2.2 Decoding part. The decoding part of the CasRel model is the core of relation extraction, and the basic idea is to extract entity-relationship triples through two steps: subject recognition and joint recognition of relations and objects. First, the subject is recognized from the input sentence, and then, all possible relations are recognized based on the subject, and the subject and object in the sentence are linked based on the relations.

(1) Subject Recognition: All possible subjects in a sentence can be identified by parsing the output vector of the encoding part. The specific operation of subject recognition is:

$$p_i^{start\_s} = \sigma(W_{start} h_i + b_{start}) \tag{7}$$

$$p_i^{end\_s} = \sigma(W_{end} h_i + b_{end}) \tag{8}$$

where h_i denotes the encoded of the i-th token in the input sequence, W is the training weight, b is the bias, σ is the activation function, $p_i^{start\_s}$ and $p_i^{end\_s}$ respectively denote the probability that the i-th token in the input sequence will be recognized as the start or the end. With two identical binary classifiers, a binary label (0/1) is assigned to each token to determine whether the token is the start or end position of the subject. A '1' is assigned if the probability exceeds a set threshold, and a '0' is assigned otherwise. Then the position of the subject s in the sequence H:

$$p_\theta(s \mid H) = \prod_{t\in\{start_s, end_s\}} \prod_{i=1}^{L} (p_i^t)^{I\{y_i^t=1\}} (1-p_i^t)^{I\{y_i^t=0\}} \tag{9}$$

where L is the sentence length, if the i-th token in H is the start position of the subject, then $I\{y_i^{start\_s}=1\}=1$, otherwise 0; if the i-th token is the end position of the subject, then $I\{y_i^{end\_s}=1\}=1$, otherwise 0. The parameters $\theta = \{W_{start}, W_{end}, b_{start}, b_{end}\}$.

(2) Joint recognition of relations and objects: the model jointly recognizes relations between subjects and objects and recognizes the objects associated with the relations. The approach to object recognition is as follows:

$$p_i^{start\_o} = \sigma(W_{start}^r (h_i + v_{sub}^k) + b_{start}^r) \tag{10}$$

$$p_i^{end\_o} = \sigma(W_{end}^r (h_i + v_{sub}^k) + b_{end}^r) \tag{11}$$

$p_i^{start\_o}$ and $p_i^{end\_o}$ respectively denote the probability that the i-th token in the input sequence is recognized as the start or the end position of the object. v_{sub}^k is the average of the encoded representation vector of all the tokens in the text between the start and the end position of the k-th subject that is recognized. Given a sequence representation H and a subject s, the probability that a word is recognized as an object o:

$$p_{\varphi_r}(o \mid s, H) = \prod_{t\in\{start_o, end_o\}} \prod_{i=1}^{L} (p_i^t)^{I\{y_i^t=1\}} (1-p_i^t)^{I\{y_i^t=0\}} \tag{12}$$

If the i-th token in H is the start position of the object, then $I\{y_i^t=1\}=1$, otherwise 0; if it is the end position of the object take the value in the same way, $\varphi = \{W_{start}^r, W_{end}^r, b_{start}^r, b_{end}^r\}$.

4. EXPERIMENTS

4.1 Datasets and performance evaluation

In this paper, an improved CasRel geographic entity relationship extraction model is constructed based on the Pytorch deep learning framework. The improved model is evaluated by the Baidu relationship extraction dataset and this paper's dataset GeoRelCorpus. The Baidu dataset consists of 55,959 training sentences, 13,418 test sentences, and 11,192 validation sentences, which contain 17 relationship types.

In this experiment, three evaluation metrics commonly used in natural language processing: accuracy, recall, and f1 score are chosen to evaluate the model in order to provide a comprehensive performance evaluation that takes into account the performance of the model in different aspects.

4.2 Experimental environment and parameter settings

The experiment is executed on the PyTorch platform, configuring with an Intel Xeon Gold 6142 CPU, an RTX 3090 GPU, Python version 3.7, PyTorch version 1.10, and CUDA version 11.2.

During training, the model's specific parameter settings encompass a maximum sentence length of 300, a batch size of 64, an LSTM dimension of 500, 4 layers of dilated CNN blocks with dilation widths of 1, 1, 2, and 4, a convolution core window size of 3, a dropout rate of 0.1, a learning rate of 0.005, and the utilization of the AdamW optimizer. These parameters were chosen based on the performance observed on the validation verification set.

4.3 Comparative experiment

In this paper, the experiments were conducted using two datasets, the Baidu relational extraction dataset, and this paper's dataset GeoRelCorpus, to compare the efficiency of CasRel-based and improved CasRel-based models, and the results of their experiments are respectively shown in Table 2.

Table 2. Experimental results for the Baidu dataset and GeoRelCorpus.

Model	Baidu dataset			GeoRelCorpus		
	Precision	Recall	F1-score	Precision	Recall	F1-score
CasRel	0.7285	0.7829	0.7548	0.7243	0.6168	0.6658
SpERTBERT	0.6909	0.7967	0.7406	0.7029	0.6243	0.6613
SpERTRoberta	0.7023	0.7956	0.7446	0.7165	0.6304	0.6701
TPLinker	0.7677	0.8063	0.7878	0.7683	0.6397	0.6986
Our model	0.8432	0.7959	0.8183	0.7953	0.6489	0.7130

The experimental results show that our model has an obvious effect improvement on both datasets compared to the CasRel model, and the F1 score is improved by about 7% on the Baidu dataset and about 5% on the dataset constructed in this paper, which proves the effectiveness of our model.

Analysis of experimental results: the introduction of multi-scale feature modules, including IDCNN, BiLSTM, and SENet, aims to capture semantic information at different levels and increase the model's ability to understand the context. In the coding part, the Roberta model is used instead of the BERT model, the Roberta uses a larger scale corpus in the pre-training process, which can provide stronger semantic representation and further enhance the model's ability to extract entity relationships. On the Baidu dataset, our model improves the F1 score by about 7% compared to the CasRel model, indicating that our model has good generalization ability on the relationship extraction task. On the GeoRelCorpus dataset, the F1 score improves by about 5%, which proves that our model has good performance on the task of entity-relationship extraction in the geographic domain.

4.4 Ablation experiments

In order to prove the effectiveness of the improved model, three sets of ablation experiments are designed in this paper, which remove IDCNN, BiLSTM, and SENet in the multiscale feature extraction module, respectively. Table 3 presents the results of the ablation experiments in the improved model on the dataset constructed in this paper.

Table 3. Results of ablation experiments.

Model	Precision	Recall	F1-score
Our model	0. 7953	0. 6489	0. 7130
Ablation IDCNN	0.7935	0.6240	0.6990
Ablation BiLSTM	0.7977	0.6315	0.7051
Ablation SENet	0.7886	0.6252	0.6978

The experimental results show that the F1 score decreases by 1.4% after the model removes the IDCNN. Since the effect of IDCNN is to increase the receptive field of the convolutional kernel and to extract local features. In the geographic entity relationship extraction task, the local context of the entities is very important for correctly determining the relationship between the entities. Removing IDCNN influences the model's ability to extract features. The F1 value decreases by 0.79% after the model removes BiLSTM. BiLSTM is able to efficiently capture contextual information and long-distance dependencies, and removing BiLSTM leads to a decrease in the model's ability to process temporal information and understand the context. The model's F1 score decreased by 1.52% after removing SENet. SENet allows the model to automatically learn the weight assignment between feature channels, and removing SENet affects the model's ability to model relationships. The results of the three sets of ablation experiments demonstrate that the components of the multi-scale feature extraction module each have unique roles and all positively impact the geographic entity relationship extraction task, further demonstrating the effectiveness of the components in the model design.

5. CONCLUSIONS

In this paper, an improved model based on the CasRel model is proposed for geographic entity relationship extraction. The performance of the improved model and the original model is compared through experiments on two datasets. The improved model enhances the ability to capture context and improves the accuracy of geographic entity relationship extraction by introducing a multi-scale feature extraction module. Through three sets of ablation experiments, the effects of each component on the model performance are analyzed and the effectiveness of each component is proved. The GeoRelCorpus dataset of this paper is constructed based on the Geography Subsection of the Encyclopedia of China and OSM labeling information, which enriches the corpus of geographic entity relationship extraction. In future research, further optimization of the model is considered to explore more effective feature extraction and relationship modeling methods; in addition, expanding the scale of the dataset, trying to introduce more geographic entity types and relationship types, and combining geographic information text and multimodal data such as maps and satellite images to construct a richer geographic entity-relationship dataset; and constructing a knowledge map of the geographic domain to improve the entity relationship extraction model in practical applications, and promote the development of more related research.

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