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A METHOD FOR EXTRACTING POWER ENTITY RELATIONSHIPS BASED ON HYBRID NEURAL NETWORKS

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Abstract. In response to the challenges of entity relationship extraction in unstructured text, the author proposes a power entity relationship extraction method based on a hybrid neural network. This method aims to overcome the limitations of existing models in accurately representing contextual environment information, thereby improving the accuracy of the extraction model to meet practical application needs. Firstly, a Bidirectional Gated Recurrent Unit (BiGRU) was designed to better capture contextual information in text sequences. This helps the model to better understand the relationships between entities. Secondly, an attention mechanism was adopted to enable the model to automatically focus on sequence features that have a significant impact on relationships. This helps the model to extract entity relationships more accurately in complex text environments. Finally, a segmented convolutional neural network (PCNN) was introduced to further improve the accuracy of relationship extraction by learning the environmental feature information in the adjusted sequence. This enables the model to better understand the contextual relationships between entities. On the publicly available English dataset SemEval2010Task8, this method achieved satisfactory results, achieving an F1 value of 85.62%. These experiments have confirmed the effectiveness of our method, providing new ideas and support for automatic extraction of entity relationships, and are expected to play an important role in the field of information extraction.

Key words: Hybrid neural network, Entity relationship extraction, Segmented Convolutional Neural Network

1. Introduction. As information technology advances swiftly and Internet-enabled mobile devices become increasingly ubiquitous, network information resources have been greatly enriched, and the most important information carrier is text data. Nowadays, the technology of obtaining Internet text information is very mature, but the scale of crawled text information is huge, and it is difficult to extract high-value information from massive text data, which greatly affects the efficiency of using existing resources. How to accurately and automatically mine key information from unstructured text becomes particularly important. In this context, Information Extraction (IE) technology emerged with the main purpose of extracting unstructured electronic texts into structured information. Information extraction mainly includes Named Entity Recognition (NER), Relationship Extraction (RE), and Event Extraction (EE) [1].

Currently, entity relationship extraction technology is garnering considerable attention in the realm of information extraction. Serving as a fundamental task across domains like information retrieval, natural language understanding, and information extraction, entity relationship extraction plays a pivotal role in discerning entity information and semantic relationships within unstructured or semi-structured text. Initially, feature-based methods were embraced and yielded promising outcomes. However, subsequent research revealed their limitations in effectively leveraging contextual structure information of entity pairs [2]. Consequently, a kernel function-based approach was proposed. Yet, due to the notable disparities in sentence structures between Chinese and English, where Chinese structures tend to be more relaxed without explicit positional cues between words, the traditional kernel function-based entity relationship extraction method fell short of achieving optimal results. In order to consider the long-distance relationships between entities in entity relationship extraction, better obtain contextual semantic information of text sequences, and extract more effective features, the author proposes a new type of relationship extraction model BiGRU Att PCNN. This model is a

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hybrid neural network model based on BiGRU and PCNN, which utilizes the BiGRU module to obtain more effective contextual semantic information of entities in text sequences; Then, using the Attention mechanism for weight allocation, automatically assign corresponding weights to the feature element based on its impact on relationship classification; After adjusting the weights, the sequence is then passed to the PCNN module. After performing the convolution operation, the pooling layer divides the convolution result into three segments based on the positions of the two entities, and then performs maximum pooling on each segment, ultimately obtaining better structural information and other related environmental features between the two entities. The experimental results show that the proposed method performs well on the publicly available English dataset SemEval 2010 Task 8 [3,4].

2. Literature Review. As deep learning continues to advance, an increasing number of neural network models are finding utility in natural language processing (NLP) endeavors. Within this landscape, entity relationship extraction methods built upon deep learning primarily encode language units of various scales using low-dimensional word vectors, and then uses neural network models such as convolution and loop to achieve automatic learning and extraction of relevant features. There is significant room for improvement in the joint entity and relationship extraction task proposed in many current studies. Heng, F. et al. introduced a novel algorithmic approach, an optimized hybrid neural network model, for predicting the multi axial fatigue life of diverse metal materials. Initially, convolutional neural networks (CNNs) are employed to extract in-depth features from a load sequence comprising critical fatigue load conditions, while preserving the time series characteristics of multi axis historical load information. Subsequently, a Long Short-Term Memory (LSTM) network is utilized to capture both the temporal dynamics and depth features extracted by the CNN. Finally, fully connected layers are employed to facilitate dimensionality transformation, enabling the prediction of fatigue life. Experimental findings demonstrate the model's efficacy in predictive accuracy and its ability to generalize well, rendering it suitable for predicting the life span of various metal materials under different loading conditions, including uniaxial, proportional multiaxial, and non-proportional multiaxial scenarios[5]. Bai, R. et al. introduced an inventive hybrid forecasting model, dubbed HKSL, designed for short-term prediction of photovoltaic power generation. This model ingeniously integrates K-means++, an optimal similar day method, and a Long Short-Term Memory (LSTM) network, leveraging historical power data alongside meteorological factors. By leveraging weather type classifications, the model identifies the most suitable similar day, which is then used as input data for the LSTM network to forecast photovoltaic power output. Validation of the hybrid model's efficacy was conducted using a dataset sourced from a photovoltaic power station in Shandong Province[6]. Zhou, D. et al. introduced a Hybrid Deep Neural Network (HDNN) tailored for active hazard recognition within civil aircraft Auxiliary Power Units (APUs). This model amalgamates Multi Time Window Convolutional Neural Network Bidirectional Long Short-Term Memory (CNN Bi LSTM) architecture to enhance performance and accuracy in hazard detection[7]. Shang, Y. M. et al. introduced a novel model named OneRel, aiming to jointly extract entities and relationships by framing the task as a fine-grained triple classification problem. This model comprises two key components: a rating-based classifier and a specialized relationship-based corner labeling strategy. The former assesses whether a token pair and their relationship form a factual triplet, while the latter facilitates a straightforward yet efficient decoding process. Extensive experiments conducted on two commonly used datasets demonstrate that the proposed approach outperforms state-of-the-art methods, consistently delivering improved performance, particularly in intricate scenarios characterized by diverse overlapping patterns and multiple triples [8].

3. Research Methods.

3.1. Joint extraction of entity relationships. Entity relation joint extraction involves combining entity recognition and relation extraction to extract structured relation triplets, such as "head entity, relation, tail entity," from unstructured text. The goal of entity relationship extraction is to accurately identify all pairs of entities with relationships in the text, and accurately identify the relationship types of each pair of entities. In Table 3.1, we provide three examples of entity relationship extraction tasks. The second column displays the original unstructured text, serving as input for the model. The desired model output is depicted in the third column of Table 1, where each relationship triplet comprises a pair of entities and a relationship. Notably, a single text sentence may contain multiple relationship triplets. Due to this, different triplets within the same

Table 3.1: Classification of Relationship Overlap Types

	Unstructured raw text	Set of entity relationship triplets	Overlap type
S1	"Under the mediation of the Li family, Qian Xuesen and Jiang Ying became a couple."	Qian Xuesen, Couple Jiang Ying	No entity overlap (NEO)
S2	"Hybrid rice expert Yuan Longping"	Yuan Longping, a professional hybrid rice expert	Single entity overlap (SEO)
S3	"Zhong Nanshan serves as a professor/executive vice director of Guangzhou Institute of Respiratory Diseases"	Zhong Nanshan, Professor at Guangzhou Institute of Respiratory Diseases	Entity pair overlap (EPO)

sentence may exhibit overlapping relationships [9].

The overlapping patterns of relationship triplets can be categorized into three types, as demonstrated in the fourth column of Table 3.1: No Entity Overlap (NEO), Single Entity Overlap (SEO), and Entity Pair Overlap (EPO). For instance, Sentence S1 exemplifies the NEO phenomenon, where the character entity "Qian Xuesen" in the sentence solely holds a marital relationship with the character entity "Jiang Ying." Conversely, Sentence S2 showcases the SEO phenomenon. The entity "Yuan Longping" in the sentence is related to the entity "Hybrid Rice Expert" and the entity "September 7, 1930", and the two triples overlap; Sentence S3 belongs to the phenomenon of entity pair overlap, and there are multiple relationships between the entity "Zhong Nanshan" and the entity "Guangzhou Respiratory Disease Research Institute" in the sentence, resulting in overlapping relationships. From Table 3.1, it can be seen that compared to the traditional task of extracting relationships between one sentence and one pair of relational entities, the task of extracting relationships with overlap is more challenging.

3.2. Entity Relationship Extraction Related Algorithms. Relationship extraction methods primarily fall into three categories: feature-based, kernel function-based, and deep learning-based approaches. (1) The feature-based method for relation extraction mainly describes the relationships between entities by extracting important features from the text, organizing them into vectors, and then using machine learning algorithms to classify the relationship features. (2) The method based on kernel function first designs a kernel function to calculate the similarity of objects in high-dimensional space, thereby obtaining structured features of objects, and then constructs a classification model based on this structured feature[10]. (3) The method based on deep learning can automatically learn text features, has little dependence on NLP tools, and can more fully utilize the structural information in the text .

3.3. Relationship Extraction Model Based on BiGRU and PCNN.

3.3.1. Framework Overview. In order to better characterize the contextual information in unstructured text and more accurately identify entity information and semantic relationship categories between entities, the author proposes the BiGRU Att PCNN relationship extraction model, which mainly consists of the Embedding layer, BiGRU layer, Attention layer, PCNN layer, and Softmax layer.

(1) Embedding layer. The word embedding training in the Embedding layer is carried out using the Word2VeC algorithm. Firstly, the word embeddings for each word are generated ω dimension vector. Moreover, to capture the positional relationships between each word and the two entities within the sentence and to leverage the syntactic and semantic nuances of the words, the author incorporated relative position features into the model. For instance, in the sentence "Sam was born in Boston," the relative distances between the word "born" and the head entity "Sam" and the tail entity "Boston" are 2 and -2, respectively, effectively reflecting their relationship within the sentence. Map these two relative distances into two randomly initialized p-dimensional position vectors. The sentence vector $S = \{q1, q2, ..., qn\}$ is represented by the real valued vector

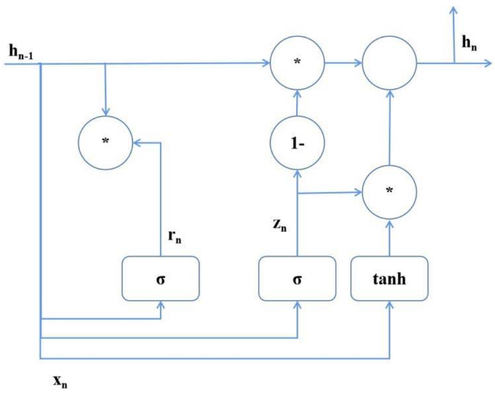

Fig. 3.1: Architecture of GRU Unit

qn of n words, where qn is the combination of the word vector of the nth word xn and the relative position vector of the entity. $S \in R^{n*d}$, where $d = w + p * 2$.

(2) BiGRU layer. The BiGRU layer is a series of GRU units that control the addition and deletion of information. GRU is a highly effective variant of LSTM, with only two gates in the model, namely the update gate and the reset gate [11]. The specific structure of GRU is shown in Figure 3.1.

In the process of information transmission, the GRU unit jointly controls the calculation of the new hidden state hn from the previous hidden state h_{n-1} by updating the value of the gate zinc and resetting the value of the gate rn, as shown in equations 3.1 to 3.4.

$$z_n = \sigma(W_z q_n + U_z h_{n-1}) \tag{3.1}$$

$$r_n = \sigma(W_r q_n + U_r h_{n-1}) \tag{3.2}$$

$$\widetilde{h_n} = tanh(W_h q_n + U_h(r_n * h_{n-1})) \tag{3.3}$$

$$h_n = (1 - z_n) * h_{n-1} + z_n * \widetilde{h_n} \tag{3.4}$$

Among them, qn and h are the inputs and outputs of the GRU unit, respectively. n is the position in the word sequence, and Wz, Wr, Wh, Uz, Ur, and Uh are all weight matrices, $\sigma()$ is a sigmoid function. Because one-way neural networks propagate information in one direction, they can only include the transmission of preceding information in that direction, but cannot obtain the following information of words in the text, which can affect the effectiveness of entity relationship extraction. Therefore, the author uses the method of bidirectional GRU neural network structure, which is composed of two unidirectional GRUs with the same structure. At each moment, the training sequence is simultaneously input into two GRU units with opposite directions, and the output result is determined by these two unidirectional GRU units together. The final output of the BiGRU layer contains complete contextual information.

(3) Attention layer. The function of the Attention layer is to weight the semantic features obtained by the BiGRU layer, and the output result vector is T={T1, T2, T3.., Tn}, where $Ti \in Rd$.

The calculation of the Attention layer is divided into three steps: similarity calculation, normalization processing, and calculating the Attention value output by BiGRU. Similarity calculation uses cosine similarity to calculate the similarity score $Score_{ij}$ between T_i and H_j, as shown in equation 3.5.

$$Score_{ij} = Sim(Ti, H_j) = \frac{Ti, H_j}{||Ti|| \cdot ||H_j||} \tag{3.5}$$

Among them, in the first round of training, the initial value of T is H.

Normalization is the process of normalizing the similarity score $Score_{ij}$ between T_i and H, as shown in equation 3.6.

$$a_{ij} = Spftmax(Sim(T_i, H)) = \frac{e^{Score_{ij}}}{\sum_{j=1}^{Lx} e^{Score_{ij}}} \tag{3.6}$$

Finally, the weight vectors $a_i = \{a_{i1}, a_{i2}, \cdots, a_{in}\}$ corresponding to T_i and H are obtained. Finally, calculate the value T of the Attention output by BiGRU, as shown in equation 3.7.

$$T = \sum_{i=1}^{n} a_i \cdot H_i \tag{3.7}$$

After weighted processing by the Attention layer, words that have a significant impact on the classification results in the statement will be given a larger weight, while words that have a smaller impact on the classification results will be given a smaller weight.

(4) PCNN layer. The PCNN layer consists of a convolutional layer and a segmented max pooling layer. In order to further identify the semantic relationships between entities, the convolutional layer in the author's model combines the output vector sequence $T = \{T1, T2, T3, .., Tnn\}$ of the Attention layer with the weight vector w for segmented convolution operations. Among them, the weight matrix w is considered as a convolutional filter. Assuming the filter length is l, then $w \in R^{l*d}$. In order to better capture more diverse features, the author's model uses m filters ($W = \{w1, w2..., wm\}$) in the convolution operation. The convolution operation involves taking the dot product of w and each l-gram in sequence T to obtain another sequence $c \in R^{n+l-1}$. The convolution operation is calculated as shown in equation 3.8.

$$C_{ki} = W_k T_{i-1+1:i} \quad 1 \leqslant k \leqslant m \tag{3.8}$$

The initial size of the convolutional output matrix C depends on the length of the sentences input into the model, while the author combines the features extracted from the convolutional layers and applies them to subsequent layers. Therefore, the final output result is no longer dependent on the length of the sentences input into the model. The relationship extraction method proposed by the author uses the segmented maximum pooling algorithm. Firstly, two entities in the input sentence are identified, and then the sentence vector is divided into three segments based on the positions of the two entities. The final result returned is the maximum value in each segment [12].

(5) Softmax layer. The function of the Softmax layer is to calculate the probability of each relationship label defined in the entity relationship extraction task, apply the Softmax function to the current output vector g of each PCNN module, generate an L-dimensional vector, that is, the number of label types is L, and then give a weighted vector z. The predicted probability of the j-th label is calculated as shown in equation (9).

$$p(y = j|g) = \frac{e^{g^T z_j}}{\sum_{l=1}^{L} e^{g^T z_j}} \tag{3.9}$$

3.3.2. Model Training and Optimization. After generating the probability distribution of each relationship category through the Softmax layer, the model is trained by minimizing the cross entropy between this probability distribution and the actual category of the relationship instance. On a given training instance Si and its label yi, the model estimates the probability of $p_j^i \in [0, 1]$ for each category. By using the Ranger optimizer to minimize the cross entropy loss between the classification result and the true category for parameter learning, the loss function is calculated as shown in equation 3.10.

$$L(S^i, y^i) => \sum_{j}^{k} l(y_i = j) log(p_j^i) \tag{3.10}$$

Table 4.1: SemEval 2010 Task 8 Dataset

relationship type	Training set	Test set
Cause-Effect(C-E)	1310(16.52%)	443(15.60%)
Component-Whole(C-W)	1002(11.43%)	317(11.06%)
Entity-Destination(E-D)	930(10.65%)	301(10.37%)
Entity-Origin(E-O)	834(9.45%)	281(10.64%)
Product-Producer(P-P)	705(8.84%)	247(9.40%)
Member-Collection(M-C)	706(8.85%)	220(8.40%)
Message Topic(M-T)	688(8.52%)	222(8.47%)
Content-Container(C-C)	623(7.84%)	250(9.50%)
Instrument-Agency(I-A)	530(6.64%)	181(7.06%)
Other(O)	503(6.20%)	145(5.63%)

Among them, l is the indicator function, $j \in \{1, 2, .., K\}$, K is the number of label types, when y '=j is true, l=1, otherwise it is 0.

In addition, the author's model adds a Drop out strategy after the BiGRU layer for regularization constraints, with the aim of shielding the neural network units with a certain probability to prevent overfitting and improve the training speed of the model.

3.3.3. Model training process. This model is aimed at relation extraction of English corpus. After the sentence sequence is input into the neural network, the embedding layer first performs word embedding training on the sentence sequence input into the neural network model, generating embedding vectors that are easy to perform numerical operations. Then input the vector into the BiGRU layer, which will extract sequence features such as the relationship between each element and its position. However, due to the distance decay of BiGRU, after the BiGRU operation is completed, the author's model adds an Attention layer to redistribute the weight of the results obtained by the BiGRU layer, that is, assign corresponding weights based on its impact on the relationship classification results, and then send them to the PCNN layer. For example, in Example 1, the weights of the two entities "report" and "role" will be raised by Attention. In PCNN, a segmented convolutional pooling operation is performed, which involves first dividing the entire sentence into three segments based on the positions of two entities, and then extracting detailed features and mutual influence information from these three segments. Finally, the Softmax layer maps the feature information to the corresponding Message Topic type, and this model ultimately forms a complete mapping of type features to types.

4. Result analysis.

4.1. Datasets. In order to verify the effectiveness of the entity relationship extraction model proposed by the author, the publicly available English dataset SemEval 2010Task 8 was used in the experiment. This dataset contains a total of 10717 corpora, including 8000 training corpora and 2717 testing corpora. The entities and their relationships have been labeled, including 9 directional relationships and 1 undirected Other type relationship. Therefore, there are 19 types of relationships, as shown in Table 4.1.

4.2. Experimental setup and evaluation indicators. The author's experiment used word vectors trained by the Word2Vec algorithm for word embedding, with a dimension of 300. Based on prior knowledge, the K parameter was set to 20, the alpha parameter was set to $4e^{-2}$, and the optimal values of other parameters were determined using a grid search algorithm on the dataset. Finally, the optimal results were achieved in the 55th to 60th iteration rounds. The optimal parameter settings for the model are shown in Table 4.2.

The author uses a confusion matrix to obtain the accuracy, recall, and F1 values for each category, and then uses the macro coverage F1 value as the evaluation metric to measure model performance based on the official documentation of the dataset.

4.3. Experimental Results and Analysis. In order to ensure the accuracy of the experiment, the same input was applied to similar relationship extraction models, and the F1 values obtained from each model were compared [13]. The F1 values obtained in each model are shown in Table 4.3.

Table 4.2: Optimal parameter settings

Parameter	Final
Batch size	127
Position vector dimension	6
Dropout rate	0.6
Hidden layer unit size	127
Number of CNN convolution kernels	100
CNN convolution kernel window length	2

Table 4.3: F1 values obtained from various models

Model	F1/%
PCNN	81.23
PCNN	80.64
BiLSTM-PCNN	83.35
BiGR U-PCNN	84.51
BiGRU-Att-PCNN	85.62
BiGRU-Att-CNN	84.25

By comparing the F1 values of each model in Table 4.3, it is clear that the performance of the model based on the hybrid neural network is better than that of a single network model. This is due to the hybrid neural network model being able to fully utilize the role of each model in relation extraction, thereby achieving multi angle coverage for feature extraction and training, and more accurately extracting relation features. For example, a single PCNN model can only focus on local features in the sequence, while a hybrid model based on BiLSTM and PCNN can first solve the word dependency problem in long sentences through the BiLSTM module, and then use the PCNN module to better capture the connections between features, ultimately extracting the features of the overall relationship instance. This design enables the hybrid model to extract relationships more effectively, resulting in better results. In addition, it can be clearly seen from the experimental results in Table 4.3 that the BiGRU-PCNN model has better relationship classification performance than the BiLSTM-PCNN model. This is because BiGRU has a simpler structure and fewer parameters compared to BiLSTM, which can retain the ability to extract sequence features and is less prone to overfitting. Therefore, the BiGRU-PCNN model performs better in relation extraction tasks [14].

The author's model incorporates an Attention mechanism for optimization based on the BiGRU-PCNN model. As shown in Table 4.3, this method achieved the highest F1 value. This is because the Attention mechanism introduced by the author can automatically align the output of the BiGRU model with the input of the PCNN model, and automatically focus on sequence elements that have a greater impact on the relationship extraction results, and redistribute their weights. This operation enables the PCNN layer to more fully utilize the output data of the BiGRU layer, thereby extracting more accurate relationship information. By observing the experimental results of the BiGRU PCNN model and BiGRU Att PCNN model on the same test set in Figure 4.1, it can be clearly seen that the F1 value variation curve of the model with the addition of the Attention mechanism has a smaller fluctuation amplitude and faster convergence speed. Under the same number of iterations, the stability of the F1 value of the BiGRU Att PCNN model is higher, and the final F1 value obtained is also higher than that of the BiGNU PCNN model. In other words, this method effectively improves the performance of the model in relation extraction tasks by introducing an Attention mechanism. This mechanism enables the model to focus more on key sequence elements, better utilize the information of input data, achieve better classification results, and improve the stability and convergence speed of the model.

In summary, we can draw the following conclusion: Introducing the Attention mechanism to redistribute the weights of the output results of the BiGRU module helps the PCNN module to obtain useful information more effectively, thereby promoting the acceleration of the iteration process. The weight redistribution function

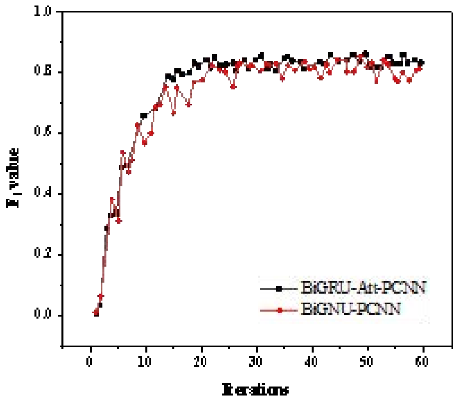

Fig. 4.1: F1 value variation curve with number of iterations

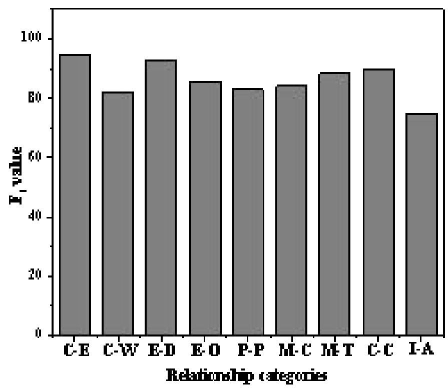

Fig. 4.2: Classification effect of different relationship types

of the Attention mechanism assigns smaller weights to information that has less impact on classification results, thereby reducing noise transmission when transmitted to the PCNN layer. This helps to reduce fluctuations during model training, so that the F1 value of the model does not change too dramatically. Furthermore, through the analysis of Figure 4.1, it can be observed that as the number of iterations increases, the F1 value of the model gradually increases. Although there are certain fluctuations, the range of fluctuations is small and overall shows a trend towards stability. This further proves that the model proposed by the author has stability [15].

4.4. Analysis of Results for Different Relationship Types. In order to explore the classification performance of the author's method on different relationship types, this experiment also counted the F1 values of 9 relationship types except for Other, as shown in Figure 4.2.

Figure 4.2 shows that the F1 values of relationship types C-E and E-D are significantly higher than those of other types, while I-A has the lowest F1 value. Further analysis of the test dataset revealed that sentences with the highest F1 value in C-E relationship types typically contain vocabulary and variants such as "cause" and "result", and are often accompanied by prepositions such as "by" and "in", exhibiting distinct structural features. Similarly, relationship type E-D also exhibits similar characteristics. Therefore, these two types of sentences are relatively easy to extract because they have clear semantic structures. On the contrary, although the I-A type with the lowest F1 value also contains high-frequency vocabulary such as "use" and its variants in the sentence, it usually only uses prepositions such as "by" and "with" when indicating tool use, which are not always accompanied by high-frequency vocabulary in the sentence. Therefore, this type of sentence lacks obvious structural features, which leads to poor performance in relation classification. In short, the prominence of structural features has a significant impact on the effectiveness of entity relationship extraction. Sentences with clear structural features are easier for the model to accurately classify, while sentences without clear structural features are more challenging.

5. Conclusion. In order to more accurately extract entity information and semantic relationship types between entities in unstructured text, the author proposes an innovative hybrid neural network model called BiGRU Att PCNN for entity relationship extraction. This model combines two neural network structures, BiGRU and PCNN. Compared with other models, it can better capture contextual semantic information in event sentences and effectively learn relevant environmental features, avoiding complex feature engineering. Although the model has achieved good results on the common English dataset SemEval 2010 Task 8, there are still some shortcomings when dealing with sentences with unclear structural features. This is because we did not fully utilize the grammatical features in the text during the relationship extraction process. Therefore, the next step of the work plan is to introduce semantic roles, parts of speech, grammatical structures and other features into the entity relationship extraction model, in order to improve the performance of entity relationship extraction. By adding more grammatical features, it is hoped to further improve the model's understanding of unstructured text, thereby more accurately identifying semantic relationships between entities and contributing more possibilities to the development of entity relationship extraction tasks.

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REFERENCES

[1] Wang, A., Liu, A., Le, H. H., & Yokota, H. (2022). Towards effective multi-task interaction for entity-relation extraction: a unified framework with selection recurrent network.

[2] Wu, C., Shi, S., Hu, J., & Huang, H. (2023). Knowledge-enriched joint-learning model for implicit emotion cause extraction. Journal of Intelligent Technology (English), 8(1), 118-128.

[3] Lin Qing-Yang, Y. F. (2023). An superheat identification method in aluminium electrolysis based on residual convolutional self-attention neural network. Journal of Northeastern University(Natural Science), 44(1), 8-17.

[4] Qin, Z., & Ge, Z. (2022). Research on entity naming algorithm for nlp based on multi-level fusion recurrent neural network. 2022 IEEE 2nd International Conference on Data Science and Computer Application (ICDSCA), 360-363.

[5] Heng, F., Gao, J., Xu, R., Yang, H., Cheng, Q., & Liu, Y. (2023). Multiaxial fatigue life prediction for various metallic materials based on the hybrid cnn-lstm neural network. Fatigue & Fracture of Engineering Materials & Structures.

[6] Bai, R., Shi, Y., Yue, M., & Du, X. (2023). Hybrid model based on k-means++ algorithm, optimal similar day approach, and long short-term memory neural network for short-term photovoltaic power prediction. The Global Energy Internet: The English version, 6(2), 184-196.

[7] Zhou, D., Zhuang, X., & Zuo, H. (2022). A hybrid deep neural network based on multi-time window convolutional bidirectional lstm for civil aircraft apu hazard identification. Chinese Aviation Journal: English edition, 35(4), 344-361.

[8] Shang, Y. M., Huang, H., & Mao, X. L. (2022). Onerel:joint entity and relation extraction with one module in one step.

[9] Chen, G., Peng, J., Xu, T., & Xiao, L. (2023). Extracting entity relations for "problem-solving" knowledge graph of scientific domains using word analogy. Aslib Journal of Information Management, 75(3), 481-499.

[10] Envelope, T. W. A., Envelope, L. Z. B., Envelope, H. L. A. B. P., Envelope, C. Z. C., Envelope, Y. S. A., & Envelope, Q. Q. D., et al. (2022). A distributed joint extraction framework for sedimentological entities and relations with federated learning. Expert Systems with Applications.

[11] Zhang, S., Ng, P., Wang, Z., & Xiang, B. (2022). Reknow: enhanced knowledge for joint entity and relation extraction. arXiv e-prints.

[12] Wang, X., Jiahao, L. I., Zheng, Z., Chang, Y., & Zhu, M. (2022). Entity and relation extraction with rule-guided dictionary as domain knowledge. Project Management frontier: English version, 9(4), 13.

[13] Popovic, N., Laurito, W., & Frber, M. (2022). Aifb-webscience at semeval-2022 task 12: relation extraction first – using relation extraction to identify entities.

[14] Han, R., Peng, T., Han, J., Cui, H., & Liu, L. (2022). Distantly supervised relation extraction via recursive hierarchy-interactive attention and entity-order perception. Neural Networks: The Official Journal of the International Neural Network Society, 152.

[15] Zhiyuan, G. E., Xiaoxi, Q. I., Wang, F., Liu, T., Guan, J., & Huang, X., et al. (2023). Annotation and joint extraction of scientific entities and relationships in nsfc project texts. Journal of Systems Science and Informatics: English edition,11(4), 466-487.

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