

Transformer Diagnostic Entity Recognition and Relationship Extraction based on Dilated Convolution and Bidirectional Graph Convolution Networks

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Abstract

As the core equipment of the power system, the stable operation of power transformers is crucial for ensuring the safety and reliability of the entire power grid. The normal operation of transformers is an important guarantee for the safety of power transportation. Transformer operation and maintenance involve a large number of technical and operational guidelines. These data sources are extensive and the format is not uniform. Knowledge graph can integrate dispersed knowledge into graph data in the form of triplets, achieving unified and standardized management of data. By constructing a transformer knowledge graph, intelligent operation and maintenance work can be achieved, reducing labor costs and improving the efficiency and quality of operation and maintenance. In recent years, there have been some achievements in the construction of knowledge graphs for power equipment. Researchers have used natural language processing technology for entity recognition and relationship extraction to construct knowledge graphs. Describing concepts, entities, events, and their relationships in a structured manner in the power system to improve the efficiency of knowledge queries and assist decision-making. However, previous transformer knowledge graph construction methods did not consider entity recognition and relationship extraction of discontinuous entities, resulting in limited semantic representation of the knowledge graph. For example, "No abnormalities in voltage regulation, medium voltage and low voltage windings". The discontinuous entities "voltage regulation winding" and "medium voltage winding" in this sentence cannot be processed by previous transformer knowledge graph construction methods. However, previous research on discontinuous entities has only focused on entity recognition tasks, and previous methods have obvious deficiencies in the recognition ability of entity boundaries. In order to solve the recognition problem of entity boundaries of discontinuous entities, this paper adopts the learnable spacing dilated convolution to adaptively capture text interval information at different distances. Secondly, for the problem of extracting relationships between discontinuous entities with incomplete entity intervals, this paper uses a bidirectional graph convolutional neural network to obtain relationship extraction feature grids from text information and entity information. In response to the characteristics of discontinuous entities with incomplete entity intervals, the relationship extraction feature grid is obtained by adding dimension functions and repetition functions to obtain the relationship extraction tensor. This article inputs the relation extraction tensor into the linear layer to predict whether a triplet holds true. Experimental results have shown that our method achieves an F1 score of 89.01% on entity recognition tasks with discontinuous entities, which is superior to previous methods; And the F1 score of the accuracy of extracting relationships between discontinuous entities with incomplete entity intervals in this article is 85.22%, filling the research gap in the task of extracting relationships between discontinuous entities.

Keywords

Transformer; Fault Diagnosis; Entity Recognition; Relation Extraction.

1. Introduction

As the core equipment in the power system, the stable operation of power transformers is crucial for ensuring the reliability of the entire power grid. With the continuous expansion of the power system, the fault diagnosis and management of transformers have become increasingly complex. A large amount of operation and maintenance text has not been fully utilized because computers are good at processing structured data. For non structured data such as operation and maintenance texts, it is necessary to convert them into structured data and form a knowledge graph in order to facilitate input into downstream tasks, such as knowledge retrieval, fault diagnosis, and operation and maintenance measures recommendation.

The essence of a knowledge graph is a graph network that represents the complex relationships between entities (concepts) in the objective world, composed of triplets as the basic unit. In a knowledge graph, entities are represented as nodes, and the relationships between entities are represented as edges connecting the nodes. The interactions between entities are depicted in the form of a graph, thus completing the structured representation of knowledge. This enables machines to understand the facts contained in textual data and achieve functions such as knowledge inference and decision-making assistance. In 2022, reference [2] proposed a knowledge extraction method of automatic model recognition and manual verification to address the challenges faced by power companies in the process of digital transformation, such as low structured transformer fault report data, shallow high-density knowledge mining hierarchy, and difficulty in sharing and applying transformer knowledge. In 2023, reference [3] proposed a method for entity and relationship extraction by extending contextual information and BERT to address the issues of blurred entity boundaries and insufficient utilization of contextual information in operational texts. Reference [4] proposes a joint entity and relationship extraction method to address the problems of weak information correlation and low decision generation efficiency in transformer operation and maintenance processes, and develops software to provide online knowledge graph automation construction, entity query, relationship query, and decision generation services. Reference [5] proposes a knowledge graph based insulation fault monitoring method for power transformers to address the issue of inconsistency between the monitoring results of transformer insulation faults and the actual situation. In 2024, reference [6] proposed a transformer defect text classification model based on CNN BiGRU Attention algorithm to address the problem of low defect processing efficiency caused by traditional transformer operation and maintenance relying on manual labor.

However, these transformer knowledge graph construction methods did not consider entity recognition of discontinuous entities, and there was no previous research on extracting relationships between discontinuous entities. This resulted in a lack of important entity and relationship information in the knowledge graph, incomplete semantic representation of transformer operation and maintenance texts, and inability to fully reflect key information such as equipment faults, defects, and interrelationships.

This article proposes a transformer fault diagnosis entity recognition and relationship extraction method based on dilated convolution and bidirectional graph convolution network for the recognition of entity boundaries of discontinuous entities and the extraction of relationships between discontinuous entities with incomplete entity intervals. This method can output entities and relationships in the input transformer operation and inspection text, creating conditions for applying knowledge graphs for transformer fault diagnosis.

2. Organization of the Text

2.1 Ontology Layer Design

In the field of knowledge graphs, ontology is a formal system used to describe concepts, categories, relationships, and constraints between them within a specific domain. The ontology defines a series of terms and concepts, and clarifies their relationships so that machines can understand and process domain knowledge. Ontology typically includes categories, attributes, instances, and relationships, which together form a structured knowledge representation framework.

The ontology layer is the core of the knowledge graph, which defines concepts, entity types, relationship types, and their mutual constraints and rules within the domain. In the field of transformer diagnosis, the ontology layer not only includes the components, fault types, diagnostic methods, and other entities of the transformer, but also covers the relationships between these entities, such as the connection relationships between components and the associations between faults and symptoms.

Entity types refer to various objects or concepts that can be identified and classified in the field of transformer diagnosis, such as transformer components, fault types, measurement parameters, etc. Each entity type has its unique attributes and features, which help distinguish and identify entities during the diagnostic process.

Relationship type describes the interactions and connections between entity types, such as the connection relationships between components, the associations between faults and symptoms, etc. Correctly defining these relationship types is crucial for understanding the operational status of transformers and conducting fault diagnosis.

The Transformer Diagnosis Corpus is a text resource library specifically built for the field of transformer fault diagnosis. It contains entity and relationship information of transformer testing and maintenance records, which is used to support transformer fault diagnosis and status analysis. In this corpus, entity categories include equipment, detect_method, operation, gas, state, operation_parameters, fault_cause, fault_class, fix_method And disposalbasis, where the equipment entity covers power equipment, transmission lines, and special locations on the equipment, such as "chromatography workstation" and "iron core"; The detection method entity includes methods used to detect faults in the power system, such as the "clamp ammeter method" and "gas chromatography method"; The operational entity describes the changes in disposal operations and indicator status, such as "purification treatment" and "power outage"; Gas entities involve describing the types of gases, such as "H₂" and "CH₄"; The status entity describes the operating status of the device, such as "normal" and "damp"; The working parameter entity includes numerical information such as voltage level and equipment capacity, such as "220kV" and "1min"; The entity description of the cause of the fault describes the reasons that led to the transformer failure, such as "deterioration of oil quality" and "dirtiness"; The fault type entity defines the type of fault, such as "low-energy discharge" and "high-energy discharge"; The disposal method entity describes the methods for handling faults, such as "cleaning" and "mechanical vibration method"; The processing basis entity involves describing the processing personnel and processing standards, such as "Guidelines for Analysis and Determination of Dissolved Gases in Transformer Oil" and "Testing Personnel".

Meanwhile, relationship categories play a bridging role in connecting entities in the transformer diagnostic corpus, including consist_of, has_content, lead_to, detect, fix, value, and append, which reveal the logical and structural relationships between entities. For example, relationships express the compositional relationships between device structures, attribute relationships reveal the connections between devices and their attributes or optional operations, resulting in causal logic between states. Detection relationships connect detection methods with device states or attributes, while repair relationships involve the connections between maintenance methods and device or device parameters. Value relationships indicate the relationships between attributes and values, while appearance relationships describe the connections between devices and phenomena or states.

2.2 Annotation Strategy

The entity recognition in this study adopts a matrix annotation strategy, and the relationship extraction adopts a five dimensional tensor annotation strategy.

Each element (i, j) of the matrix for entity recognition tasks represents an interval of text [i, j], with the value k being the type of interval. For the annotation problem of real labels in entity recognition, W2NER[7] adopts "Next Neighboring Word" (NNW), "Tail Hand Word - *, THW - *, * representing the entity type of the entity from the end position to the start position" (THW - *, * represents the entity type of the entity), and "Cannot be used as an entity" as interval types to solve the annotation problem of discontinuous entities. The entity type used in the entity recognition task of this article has been explained in 2.1. Based on this, this article slightly adjusts the types of intervals in the W2NER method, using "Head Tie Word - *, HTW - *, * representing the entity type of the entity from the starting position to the ending position" to indicate the interval and entity type where the entity is located, "Prior Neighboring Word (PNW)" to indicate the character composition association of discontinuous entities, and "Cannot be used as an entity (O)" to indicate that an interval cannot be used as an entity interval.

The annotation method for relation extraction task adopts a five dimensional tensor annotation, where the position of the five dimensional tensor (i, j, k, m, n) represents a triplet with the entity interval of the head entity being [i, j], the relationship type being k, and the entity interval of the tail entity being [m, n]. The value at each position of the five dimensional tensor indicates whether the triplet holds, with a value of 1 indicating that the triplet holds and a value of 0 indicating that the triplet does not hold.

In response to the problem of extracting relationships between discontinuous entities whose entity intervals are not completely identical, this paper treats the entity interval as a single entity and cannot represent an entity solely based on its starting or ending position. This is because when two discontinuous entities have the same ending position, labeling the end position of the entity can cause ambiguity and cannot distinguish between the two entities. However, the drawback of this design in this article is that it cannot annotate the relationship between discontinuous entity pairs with the same entity interval, which is a limitation of this article.

The annotation method for the relationship extraction task in this article adopts a five dimensional tensor annotation instead of a four-dimensional or lower dimensional tensor, because a pair of entities may have multiple types of relationships. In a four-dimensional tensor, only one relationship type can be annotated, and lower dimensional tensors cannot represent this situation. Therefore, the annotation method for the relationship extraction task in this paper adopts annotation for a 5-dimensional tensor.

Taking "No abnormalities in voltage regulation, medium voltage and low voltage windings" as an example, Figure 1 shows the entity labeling strategy in this paper, and formula (1) shows the relationship represented in this paper (voltage regulation windings, appearance, No abnormalities).

	No	abnormalities	in	voltage	regulation	,	medium	voltage	and	low	voltage	windings
No	O	HTW-state	O	O	O	O	O	O	O	O	O	O
abnormalities	PNW	O	O	O	O	O	O	O	O	O	O	O
in	O	O	O	O	O	O	O	O	O	O	O	O
voltage	O	O	O	O	O	O	O	O	O	O	O	HTW-equipment
regulation	O	O	O	PNW	O	O	O	O	O	O	O	O
,	O	O	O	O	O	O	O	O	O	O	O	O
medium	O	O	O	O	O	O	O	O	O	O	O	HTW-equipment
voltage	O	O	O	O	O	PNW	O	O	O	O	O	O
and	O	O	O	O	O	O	O	O	O	O	O	O
low	O	O	O	O	O	O	O	O	O	O	O	HTW-equipment
voltage	O	O	O	O	O	O	O	O	PNW	O	O	O
windings	O	O	O	O	PNW	O	O	PNW	O	O	PNW	O

Figure 1. Typical case of entity recognition annotation

The first row and first column in Figure 1 represent text, while the letters below the text are type labels for intervals, such as "O" indicating that an interval cannot be used as an entity interval; The position "PNW" in the third row and second column indicates that the corresponding word "anomalies" in the third row is a character of the entity, and the word before this character in the entity is the corresponding word "No" in the second column; The position "HTW state" in the 5th row and 13th column indicates that the character "voltage" corresponding to the 5th row is the first character of the entity, while the character "wins" corresponding to the 13th column is the last character of the entity. The discontinuous entity "voltage regulation wins" can be determined by first searching for the "HTW - *" label to determine the entity's interval, then starting from the last character and querying the previous character through the "PNW" label, finally finding the starting character of the entity, and obtaining the textual representation of the entity "voltage regulation wins".

$$t(3,11,1,0,1) = 1 \tag{1}$$

In formula (1), the five dimensional tensor of the relation extraction task represents the true label of the triplet's establishment, with the first two input values being the interval of the head entity [3,11], the third input value "1" being the index of the relation type "appearance", and the last two input values being the interval of the tail entity [0,1]. The value of '1' indicates that the triplet is valid, while the value of '0' indicates that the triplet is not valid.

3. Joint Extraction Model

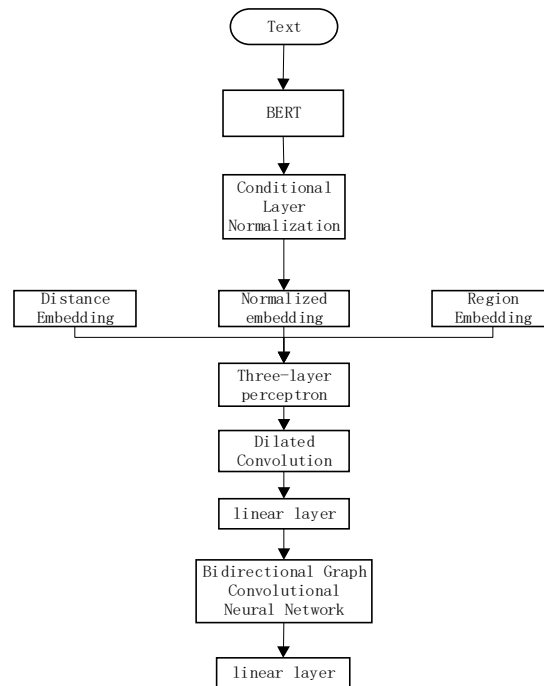


Figure 2. Joint Extraction Model Framework

The framework architecture considered in the paper, as shown in Figure 2, includes an entity recognition module and a relationship extraction module. In order to perform entity recognition tasks, this paper adopts the method of constructing word pairs in the W2NER model, and then uses learnable spacing dilated convolutions to capture information from text intervals at different distances, solving the problem of low accuracy in entity boundary recognition caused by the fixed dilation rate of the receptive field of dilated convolutions in previous methods. Linear layers are then used to calculate the types of all intervals in the text. To perform the relationship extraction task, a bidirectional graph convolutional neural network is first used to obtain the feature grid for relationship extraction. In

response to the characteristics of discontinuous entities with incomplete entity intervals, the relationship extraction feature grid is obtained by adding dimension functions and repetition functions to obtain the relationship extraction tensor. This article inputs the relation extraction tensor into the linear layer to predict whether a triplet holds true.

The specific process of this article is as follows. In the entity recognition module, the text is first input into the bidirectional encoder representation BERT from the transformer to obtain the word vector sequence of the text. Then, using the W2NER framework to construct word pairs, the bidirectional encoder represents the word vector sequence output by the model and inputs it into the conditional normalization layer to obtain normalized embeddings. Concatenate distance embedding, region embedding, and normalized embedding, and then fuse these information through a three-layer perceptron to obtain a word pair representation with position and region perception. Input word pairs into learnable spacing dilated convolutions to capture information from text intervals at different distances, and then feed them into linear layers to calculate entity boundaries and types. In the relationship extraction module, the entity recognition results are combined with the word pair grid through a bidirectional graph convolutional network to extract feature matrices and task shared feature matrices. These matrices are then fed into a three-layer perceptron and normalized exponential function classification to obtain preliminary relationship extraction results. Then input the preliminary relationship extraction results into a bidirectional graph convolutional neural network weighted by relationships. The output matrix of the bidirectional graph convolutional network weighted by relationships is obtained by adding dimension functions and repeating functions to obtain the relationship extraction tensor. The first two dimensions represent the intervals of the head entity, the third dimension represents the relationship type, and the fourth and fifth dimensions represent the intervals of the tail entity. Input the relation extraction tensor into the linear layer to determine whether this triplet holds. For the results of entity recognition and relationship extraction, this paper uses threshold hyperparameters for entity prediction and relationship prediction to filter out knowledge graph triplets, and outputs entity triplets of the text. An example of using maintenance records to construct a knowledge graph and perform knowledge representation is as follows: "No abnormalities in voltage regulation, medium voltage and low voltage windings". The entity recognition module in this article can extract the discontinuous entities "voltage regulation windings" and "medium voltage windings", as well as the continuous entities "low voltage windings" and "no abnormalities" in this sentence. The relationship extraction module in this article can extract knowledge graph triplets from this record, such as: (voltage regulation windings, appear, No abnormalities), (medium voltage windings, appear, No abnormalities), (low voltage windings, appear, No abnormalities). According to the knowledge graph triplet, the knowledge graph of the text can be obtained, as shown in Figure 3.

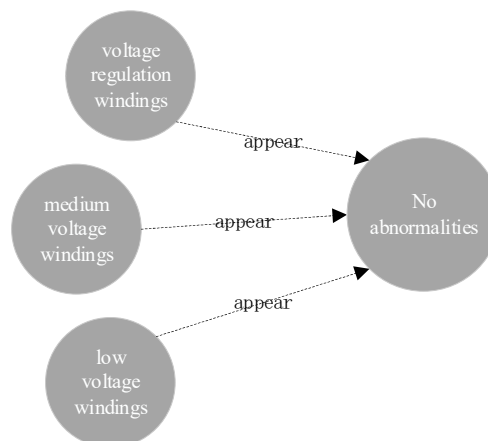


Figure 3. Knowledge graph containing typical cases of discontinuous entity text

3.1 Entity Recognition

The W2NER model [7] solves the problem of entity recognition for discontinuous entities by using word to grid and multi granularity dilated convolution methods. However, the W2NER method uses multi granularity dilated convolutions to capture text interval information at different distances, which limits the recognition ability of entity boundaries. Ismail Khalfaoui Hassani et al. proposed the learnable spacing dilated convolution DCLS [1], which uses the positions of non-zero elements in the convolution kernel as learnable parameters and combines Gaussian interpolation function to adaptively expand the receptive field of dilated convolution. The entity recognition module in this article replaces W2NER's multi granularity dilated convolutions with learnable spacing dilated convolutions. Through learnable spacing dilated convolutions, it adaptively captures text interval information at different distances and improves the accuracy of knowledge graph entity recognition without increasing the number of model parameters.

The W2NER model uses the conditional layer of the word vector sequence output by BERT (Bidirectional Encoder Representation from Transformer) and BERT style grid representation to construct the word pair grid $C \in \mathbb{R}^{N \times N \times d_c}$.

The position (i, j) of the word pair grid represents word pairs, indicating the feature dimension of each word pair. In order to adaptively capture text interval information at different distances, this paper uses learnable spacing dilated convolution DCLS, which can be calculated as formula (2).

$$Q = \text{GELU}(\text{DCLS}(C)) \quad (2)$$

In formula (2), Q is the word pair grid; GELU is a Gaussian error linear unit used as the activation function.

Due to the insufficient amount of text in the dataset of this article, excessive model layers can lead to overfitting. Therefore, this article chooses linear layers for entity recognition to avoid overfitting caused by excessive model layers.

Based on the word pair grid Q , a linear layer is used to calculate the probability e_{ij}^k of the type k of interval [i, j], where i, j represents the starting and ending positions of the entity in the text, Q_{ij} as input, as shown in formula (3).

$$e_{ij}^k = \text{Linear}_1(Q_{ij}) \quad (3)$$

In the formula, Linear_1 represents the linear layer.

3.2 Relation Extraction

In order to combine entity information with text information for relationship extraction, this article adopts the message passing mechanism of bidirectional graph convolutional neural network to obtain the feature grid of text relationship extraction by using the word pair grid C of text and the result e of entity recognition. Extract the initial values Z^0 of the feature grid for the graph convolutional network using the word pairs of the text in grid C , as shown in formula (4).

$$Z^0 = C \quad (4)$$

Let Z^p be the feature grid for extracting relationships in the p-th layer, N be the total number of words in the sentence, E be the type label set for the interval, and \bar{W}_k^p and \bar{b}_k^p be the forward graph convolution kernel parameters and biases for the p-th layer, respectively. \bar{W}_k^p and \bar{b}_k^p are the parameters and biases of the backward graph convolution kernel for the p-th layer, respectively. The formulas for updating the relational feature grid in a bidirectional graph convolutional network are (5), (6), and (7):

$$\bar{Z}_{ij}^{p+1} = \text{ReLU} \left(\sum_{j \in N} \sum_{k \in E} e_{ij}^k \left(\bar{W}_k^p Z_{ij}^p + \bar{b}_k^p \right) \right) \quad (5)$$

$$\bar{Z}_{ij}^{p+1} = \text{ReLU} \left(\sum_{j \in N} \sum_{k \in E} e_{ji}^k \left(\bar{W}_k^p Z_{ij}^p + \bar{b}_k^p \right) \right) \quad (6)$$

$$Z_{ij}^{p+1} = \left[\bar{Z}_{ij}^{p+1} \oplus \bar{Z}_{ij}^{p+1} \right] \quad (7)$$

In formula, \bar{Z}_{ij}^{p+1} and \bar{Z}_{ij}^{p+1} respectively represent the forward and backward message transmission results of the type of interval $[i, j]$; ReLU is a linear rectification function used as the activation function; Z_{ij}^{p+1} is the feature representation vector of the entity interval (i, j) at the p+1th layer; \oplus is the vector concatenation operation.

Based on the characteristics of discontinuous entities, an entity interval is used as a unique identifier for an entity, and a five tuple a is constructed to represent a triple (head entity, r, tail entity), where the entity interval of the head entity is $[i, j]$, the entity type is r , and the entity interval of the tail entity is $[m, n]$. In order to solve the problem of extracting relationships between discontinuous entities with incomplete entity intervals, this paper uses graph convolutional neural networks to extract relationship extraction feature grids from text. The feature grids G are expanded from (N, N, d) to $(N, N, |R|, N, N, d)$ using an increase in dimensionality function (unscueze) and a repeat function (repeat), resulting in a relationship extraction tensor. Here, d is the dimension of the relationship extraction feature grid, and $|R|$ represents the number of sets of all entity types. In order to identify whether the triplet (head entity, r, tail entity) with entity interval $[i, j]$, entity type r , and entity interval $[m, n]$ of the head entity holds, G is input into the linear layer for relationship extraction, as shown in formula (8).

$$t(i, j, r, m, n) = \text{Linear}_2(G) \quad (8)$$

In formula (8), Linear_2 is a linear layer; $t(i, j, r, m, n)$ represents the probability that the entity interval of the entity is $[i, j]$, the entity type is r , and the entity interval of the tail entity is $[m, n]$.

3.3 Training and Reasoning

During the training phase, the goal of this article is to minimize the loss function L of the model, which consists of two parts: L_{ner} for the entity recognition module and L_{re} for the relationship extraction module. The definition of the loss function is shown in formulas (9), (10), and (11):

$$L_{ner} = -\frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N \sum_{k=1}^{|E|} \hat{e}_{ij}^k \log e_{ij}^k \quad (9)$$

$$L_{re} = \sum_{\hat{t}(i,j,r,m,n) \in \{0,1\}} \text{BCELoss}(\mathbf{t}(i,j,r,m,n), \hat{\mathbf{t}}(i,j,r,m,n)) \quad (10)$$

$$L = L_{ner} + L_{re} \quad (11)$$

In formula (9), (10), and (11), N represents the number of words in the sentence; \hat{e}_{ij}^k is the probability that the entity type of word a has a true label of k ; e_{ij}^k is the probability that the predicted entity type for word a is k ; E is a set of interval types; k is the k th interval type in E ; BCELoss is the binary cross entropy loss function; $\hat{\mathbf{t}}(i, j, r, m, n)$ represents the true label of the triple where the entity interval of the head entity is $[i, j]$, the entity type is r , and the entity interval of the tail entity is $[m, n]$.

In the model training process of this article, due to the multi classification problem of entity recognition, the loss function of the entity recognition module L_{ner} uses the cross entropy loss function. Due to the use of multi label classification in the relationship extraction module to solve the problem of overlapping relationship recognition, the loss function of the relationship recognition module L_{re} adopts a binary cross entropy loss function. Adam is used as the optimization algorithm during the training phase of this article.

In the inference stage, this article combines the results from entity recognition and relationship extraction modules to extract knowledge graph triplets. For each triplet prediction $(s_{i,j}^k, r, o_{m,n}^{k'})$, where r is the relationship label, k and k' are the entity type labels, indices i, j and m, n are the starting and ending indices of the head entity s and tail entity o , respectively. This paper applies the conditions of formula (12) to determine whether a triplet is valid: in the inference stage, this paper combines the results from the entity recognition and relationship extraction modules to extract knowledge graph triplets. For each triplet prediction, where r is the relationship label, k and k' are the entity type labels, indices i, j and m, n are the starting and ending indices of the head entity s and tail entity o , respectively. This paper applies the conditions of formula (12) to determine whether a triplet is valid:

$$e_{ij}^k \geq \lambda_e; e_{mn}^{k'} \geq \lambda_e; \mathbf{t}(i, j, r, m, n) \geq \lambda_r \quad (12)$$

In formula (12), λ_e is the threshold hyperparameter for entity recognition, which is set to 0.5 in this paper; λ_r is the threshold hyperparameter for relation extraction, which is set to 0.5 in this article.

By using threshold hyperparameters for entity recognition and relationship extraction, this paper can effectively filter out low credibility triplets and extract structured entities and relationships.

4. Experiment

4.1 Datasets

This article extracts relevant data from "Fault Diagnosis and Case Studies of Large Power Transformers", "Intelligent Transformer Design and Engineering Applications", and related literature. The data is annotated using the annotation tool doccano to obtain an information extraction dataset for transformer operation and maintenance. According to statistics, the dataset contains a total of 7528 texts and 1175523 characters. There are 3107 discontinuous entities, accounting for 13% of the

entities in the dataset. The number of relationships related to discontinuous entities is 6141, accounting for 3% of the total number of relationships. Use 80% of the dataset for training and the rest for testing. The statistical information of entity types is detailed in Table 1, and the statistical information of relationship types is detailed in Table 2.

Table 1. Entity type statistical information

Entity type	Number
state	1317
operation_parameters	10470
equipment	6743
fault_class	366
operation	3048
fault_cause	120
fix_method	108
disposal_basis	213
detect_method	687
gas	828

Table 2. Relationship type statistical information

Entity type	Scheme 1
has_attribute	12730
appear	1335
consist_of	3032
lead_to	2184
value	747
detect	386
fix	56

In order to verify the effectiveness of the method proposed in this paper in solving the problem of entity recognition of discontinuous entities, this paper used datasets CADEC, ShARe14, and our own dataset containing discontinuous entities in the experiment of entity recognition of discontinuous entities.

4.2 Parameter Selection

Table 3. Model parameters settings

Parameter Name	Value
Batchsize	1,2
Learning rate	0.001 ,0.0001
The number of layers in a bidirectional graph convolutional network	0,1,2,3

This article verifies the performance of the model under different hyperparameter settings through experiments, and ultimately determines the optimal model parameter configuration. The parameter range of the experiment and the selected optimal parameters (indicated in bold) are detailed in Table 3.

4.3 Parameter Selection

In order to verify the effectiveness of the method proposed in this paper in solving the problem of entity recognition of discontinuous entities, we selected the entity recognition method W2NER [7] (Method 1) for discontinuous entities, and the entity recognition method based on span overlapping entities and discontinuous entities [8] (Method 2), and compared entity recognition using multiple datasets containing discontinuous entities (CADEC, ShARe14, and the dataset proposed in this paper). Using F1 score as the evaluation index, the comparative experimental results in Table 4 are obtained.

Table 4. Experimental results of entity recognition for discontinuous entities

Model name	Dataset name		
	CADEC	ShARe14	This article's dataset
Method 1	73.18	82.29	87.04
Method 2	69.41	81.25	85.42
Proposed method in this artical	75.23	85.20	89.01

Method 1 uses fixed dilation rate dilated convolution, which limits the receptive field of dilated convolution and is not conducive to entity boundary recognition.

Method 2 adopts the construction of span maps and multi-layer perceptrons for entity recognition, without considering the interaction between words within the span, which is not conducive to identifying the constituent words of discontinuous entities.

This method uses learnable spacing dilated convolution to adaptively adjust the receptive field and solve the problem of entity boundary recognition. Therefore, its performance on these datasets containing discontinuous entities is better than other methods. In addition, on the dataset of this article, the F1 score of the proposed method in relation extraction is 85.22%, which verifies the effectiveness of the proposed method in solving the task of relation extraction for discontinuous entities with different entity intervals.

Table 5. Experimental results of entity recognition and relationship extraction

Model name	Entity Recognition			Relation Extraction			Joint F1 score
	P	R	F1	P	R	F1	
Method 3	93.18	92.59	93.04	91.59	92.28	91.24	92.14
Method 4	82.15	81.75	83.42	79.48	79.15	78.25	80.84
Method 5	84.15	84.75	84.42	85.48	86.15	84.25	84.36
Proposed method in this artical	90.97	91.14	90.01	87.35	86.01	87.21	88.61

To verify the effectiveness of the proposed method in entity recognition and relationship extraction, PFN (Partition Filter Network [9], Method 3), Transformer Fault Knowledge Graph Construction Method based on Bidirectional Graph Convolutional Network [4] (Method 4), and Joint Entity and Relationship Extraction (SpERT) based on Span and Bidirectional Encoder Representation Model

[10] (Method 5) were selected as comparative algorithms. Due to the fact that the comparison method cannot represent discontinuous entities, samples containing discontinuous entities in the dataset of this article do not participate in the effectiveness experiments of entity recognition and relationship extraction. This article uses accuracy P, recall R, and F1 score as evaluation indicators to obtain experimental results in Table 5.

Result analysis:

Method 3 uses a partition filter encoder to solve the error accumulation problem in entity recognition and relationship extraction. However, the feature interaction between the entity recognition task and the relationship extraction task in this article is unidirectional, and there is a problem of error accumulation caused by the interference of entity recognition errors in the relationship extraction task. Therefore, the performance is not as good as method 4.

The BIO sequence annotation method for entity recognition task in Method 4 requires more categories to be classified than in this paper, and the long short-term memory network has weaker ability to capture distant information than close distance information, resulting in weaker recognition ability for entities with longer text lengths.

Method 5 involves enumerating all possible entity intervals in the input sentence, classifying each possible entity interval into entity types, and then classifying all possible entity pairs into relationships. However, this method sets the maximum length of entities, which imposes a length limit and makes it difficult to recognize longer entities.

This method captures text interval information at different distances on a word pair grid through learnable spacing dilated convolution, solving the problem of entity boundary recognition. Therefore, the entity recognition performance is better in comparative experiments. Although the method proposed in this article has problems such as poor performance in relation extraction, a large number of parameters, and high computational complexity, it is unique in solving the problem of relation extraction for discontinuous entities with incomplete entity intervals.

4.4 Ablation Experiment

In this section, this article analyzes the impact of learnable spacing dilated convolution and bidirectional graph convolution networks on model performance, using the joint F1 score as the evaluation metric, and obtains the ablation experimental results in Table 6.

Table 6. Results of ablation experiment

Component	settings	Joint F1 score
Dilated convolution	dilation rate=1	82.91
	dilation rate=2	86.94
	dilation rate=3	84.42
	DCLS	88.61
bidirectional graph convolution networks	1 layer	86.56
	2 layers	88.61
	3 layers	87.25

Firstly, this article uses dilated convolutions with different dilation rates to verify the impact of learnable spacing dilated convolutions on model performance. According to Table 6, the performance of models using dilated convolutions with different dilation rates varies, indicating that the ability of dilated convolutions to capture contextual information is related to their dilation rate. Due to the fact

that the learnable spacing dilated convolution in this article achieves adaptive expansion of the receptive field of dilated convolution through Gaussian interpolation, the performance of this method is higher than that of dilated convolution with fixed expansion rate.

Then, this article uses bidirectional graph convolutional networks with different layers to verify their effectiveness in improving model performance. According to Table 6, when the number of layers in the bidirectional graph convolutional network is set to 2, the joint F1 score of the model is higher than when the number of layers in the bidirectional graph convolutional network is set to 1. However, the deeper the number of layers in the bidirectional graph convolutional network, the more samples and parameters the model requires. Given that the dataset size in this article is insufficient to meet the sample size requirements of a 3-layer or higher bidirectional graph convolutional network, the joint F1 score of the model using a 3-layer bidirectional graph convolutional network is lower than that of the model using a 2-layer bidirectional graph convolutional network. Therefore, this article adopts a two-layer bidirectional graph convolutional network as a compromise between the number of datasets and model performance.

In summary, these ablation experimental results indicate that the learnable spacing dilated convolution and bidirectional graph convolution networks proposed in this paper can effectively improve model performance.

5. Conclusion

This article proposes a transformer fault diagnosis entity recognition and relationship extraction method based on dilated convolution and bidirectional graph convolution network for the recognition of entity boundaries of discontinuous entities and the extraction of relationships between discontinuous entities with incomplete entity intervals. It can recognize discontinuous entities in transformer operation and maintenance texts and extract relationships between discontinuous entities with incomplete entity intervals. The core contributions and conclusions of the research are as follows:

- 1) Using learnable spacing dilated convolution to adaptively expand receptive field and solve entity boundary recognition problem.
- 2) A joint extraction model based on dilated convolution and bidirectional graph convolutional network is proposed to solve the problems of entity recognition of discontinuous entities and relationship extraction of discontinuous entities with incomplete entity boundaries, filling the research gap in the task of relationship extraction of discontinuous entities.

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