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FEATURE ENHANCEMENT BASED JOINT EXTRACTION OF WEB NOVEL ENTITY RELATIONSHIPS

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Abstract. In an era characterized by constant advancements in computer science, web novels represent an extensive and intricate form of text that presents unique challenges for automated processing. This investigation aims to address the issues associated with the time-intensive, laborious, and error-prone nature of text processing within web novels. It presents a novel joint entity-relationship extraction model that is enhanced by various features. By leveraging a combination of computer vision and natural language processing techniques, the extraction of named entities and relationships is modeled in a unified framework to optimize text feature mining. The employment of bidirectional long-short term memory networks and multi-layer perceptron equips the model with the capability to effectively extract entity relationships from web novels comprehensively. Experimental outcomes indicate that the model achieves an F1 score of 72.4%, marking a notable enhancement over traditional pipelined models. This study offers robust tools and methodologies for computers to process extensive and complex textual data, further integrates computer vision with natural language processing, and broadens the potential applications within the domain of information processing.

Key words: entity-relationship extraction, pre-trained models, feature enhancement, natural language processing

1. Introduction. In this paper, a feature-enhanced entity-relationship joint extraction model based on feature augmentation is proposed to cope with the time-consuming, labor-intensive, and error-prone problems in text processing for web novel texts. Web novels typically provide detailed descriptions of characters' personalities and destinies, along with intricate social interactions. However, their length and complex character relationships can hinder storyline comprehension and offer an unsatisfactory reading experience. Therefore, employing deep learning technology to transform complex text into structured information can help readers quickly grasp the plot of web novels and gain an overall understanding of the characters and relationships involved [1].

Named Entity Recognition (NER) focuses on extracting entities of specific categories from unstructured text, with common entity types including time, location, person, organization, etc. Relationship extraction aims to identify the relationships between entities within a text [2]. Considering the limitations of pipelined models, a joint approach that integrates named entity recognition and relationship extraction has been proposed [3]. This approach considers the correlation between entities and relationships while performing entity recognition and entity-to-relationship classification, thereby improving the model's recognition efficiency and reducing error accumulation [4].

This study presents a feature enhancement-based model for extracting relationships between entities in web novels. The model utilizes BERT for pre-processing training data to obtain word vectors, and then annotates entity features using the language technology platform released by Baidu for lexical annotation of words in a sentence [5]. Multiple features are input into the model together for training. Additionally, a decomposition strategy is employed to first identify the head entity, followed by predicting the corresponding tail entity and relationship category. The shortcomings of existing studies are the problems of error accumulation, relationship overlap and information redundancy in information extraction methods, the error propagation in traditional pipeline models that degrade the overall extraction performance, and the limitations of the joint entity-relationship extraction methods proposed in recent years. In terms of innovativeness, the thesis proposes a joint entity-relationship extraction model based on feature augmentation, introduces named entity and lexical

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labeling features, employs decomposition strategy and multi-attention mechanism, and achieves remarkable results in entity-relationship extraction tasks in the field of online literature. In addition, the paper further integrates computer vision and natural language processing techniques, provides effective tools for processing large-scale complex text data, and expands the application prospects in the field of information processing.

2. Related work. Current information extraction methods include entity recognition and relationship extraction, but these methods have some problems such as error accumulation and relationship overlap. To solve these problems, the researchers proposed joint entity-relationship extraction method.Information Extraction [6] (IE) involves structuring natural language text to extract valuable information from it. In the past, Named Entity Recognition (NER) and Relation Extraction (RE) were considered as separate tasks. Research conducted by Deng Yuyang et al. [7] revealed that a pre-trained model enhanced the F1 value of word vectors by 5.9% over Bi-directional Long Short-Term Memory (BiLSTM) and Conditional Random Field models. Agrawal Ankit et al. [8] demonstrated that the BERT pre-trained model, after tuning on GENIA, achieved F1 values of 74.38% on GermEval 2014, 85.29% on GermEval 2014, and 80.68% on JNLPBA dataset, which is suitable for complex named entity recognition. BACH and BADASKAR [9] developed the extraction model JPEA, and the combination of a pre-trained model and attention mechanism significantly enhanced semantic expression ability as well as the accuracy of ternary extraction. HAN and WANG [10] integrated Bi-directional Gated Recurrent Unit (BiGRU) and CNN into an entity-relationship extraction model, offering a new approach to entity-relationship extraction in the information extraction field.

However, this method is simplistic and faces several challenges: error accumulation, where the correlation between the two tasks is overlooked during information extraction, leading to varying relationship extraction results based on named entity recognition outcomes; overlapping relationships, where a single entity corresponds to multiple entities with various relationships superimposed; and information redundancy, where not all recognized entities have corresponding entities and relationships, resulting in information redundancy and reduced recognition efficiency.

To address these issues, joint entity-relationship extraction methods have been proposed [11]. Unlike traditional pipelined models that first identify entities and then perform relationship classification on target entity pairs, these methods simultaneously model named entity identification and relationship extraction to mitigate the impact of error propagation and enhance overall extraction performance.

In recent years, joint models for entity-relationship extraction have also been developed, with strategies including parameter-sharing-based joint extraction methods and sequence annotation-based joint extraction methods. WANG et al. [12] addressed the multi-entity-relationship problem frequently encountered in food public opinion by extracting entity-relationship types from BERT and incorporating a semantic role-attention mechanism to integrate entity-relationship types in BiLSTM for entity-relationship extraction in food public opinion. XU and ZHAO [13] proposed a joint extraction model integrating BiLSTM and ResNet to obtain word context vectors, utilizing residual network features to capture entity pair structural information with maximum pooling. WANG and LIU [14] introduced a pointer annotation strategy-based approach to tackle entity nesting issues, achieving significant results with F1 values exceeding 70% on average across two Chinese corpus datasets. Fan and associates employed a multi-window convolutional neural network to automatically extract sentence features and utilized entity type embedding methods to classify relationships, ultimately outputting eleven extracted relationships in ternary group format with a model F1 value reaching 93.15%. Xueying Wu and colleagues proposed a BERT-based Hierarchical Tagging Model (HtERT) for relational ternary extraction in the geological domain, utilizing BERT-wwm as the underlying encoder, limiting entity extraction length, and incorporating global information and BiLSTM to extract accurate geological sample features, enhancing the extraction capabilities for relationship triples as well as overlapping triples.

2.1. Knowledge map. Knowledge Graph aims to integrate structured and unstructured information on the Internet to construct a knowledge graph for modeling, reasoning and associating knowledge. The construction of knowledge graph usually involves techniques such as entity recognition, relationship extraction and knowledge reasoning. Classical entity-relationship extraction methods include rule-based methods and statistical learning-based methods. In recent years, deep learning methods such as neural networks have been widely used in the construction of knowledge graphs, such as using models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for entity recognition and relationship extraction [15].

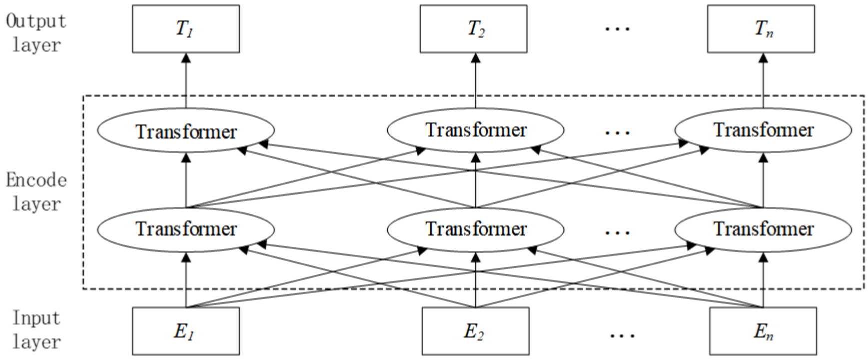

Fig. 3.1: BERT pre-trained language model

2.2. Information Extraction. Information extraction aims to automatically extract structured information from unstructured text. Information extraction includes subtasks such as entity recognition and relationship extraction. Traditional information extraction methods mainly use a pipeline model, i.e., entity recognition is performed first, and then relationship classification is performed between the recognized entities. However, this pipeline model suffers from problems such as error accumulation and relationship overlap. To solve these problems, in recent years researchers have proposed joint entity-relationship extraction methods, such as parameter sharing and sequence labeling. These methods jointly model the entity recognition and relationship extraction tasks to improve the overall performance of the model [16].

3. Feature Enhancement Based Joint Extraction of Entity Relationships. The model that emphasizes on feature enhancement is primarily composed of three sections: an input layer, a head entity recognition layer, and a tail entity and relationship recognition layer. The input layer provides a rich and comprehensive textual feature representation for the model; the head entity recognition layer encodes the input text and determines the location of the head entity; the tail entity and relationship recognition layer further predicts the tail entity and relationship on the basis of the head entity. The whole model realizes joint entity-relationship extraction through the transfer of head entity and tail entity information, reflecting the close intrinsic connection between the parts. At the input layer, the model undergoes pre-training with BERT and is then integrated with the extracted named entities and lexical annotation features to acquire text feature information. Subsequently, the head entity encoding vector is derived via the head entity recognition layer. Thereafter, the text encoding information is combined with the multi-head attention mechanism to achieve comprehensive recognition of tail entities and relationships, ultimately yielding the entity-relationship extraction triad.

3.1. BERT pre-training model. BERT [17] is a profound bidirectional language representation model that utilizes the Pre-training plus Fine-tuning training method. It pre-trains the language model with the main architecture of the multi-layer Transformer's Encoder layer, surpassing previous shallow inter-embedding models based on single language models and multiple single models. The structure of the BERT pre-training language model is presented in Fig 3.1.

Utilizing the BERT language model for feature extraction from processed text and recognized domain-specific dictionaries. The model accepts input ranging from a single sentence to extensive texts, with 'CLS' indicating the start and 'SEP' marking the end of the text. Word embeddings involve transforming each word into vector form; sentence embeddings determine the sentence membership of each word, capturing overall semantic content; and position embeddings encode the spatial information of words. A representation of the encoding process for the example sentence 'Bai Xiaochun departed from the Lingxi Sect' is illustrated in Fig. 3.2.

After vectors illustrate the sentence's words, they need to be feature-coded. BERT uses the Encoder part of the classic Transformer architecture. Post multi-head attention, text is transferred from the Encoder input to a feed-forward neural network. A supplementary attention layer in the decoder focuses on information linked

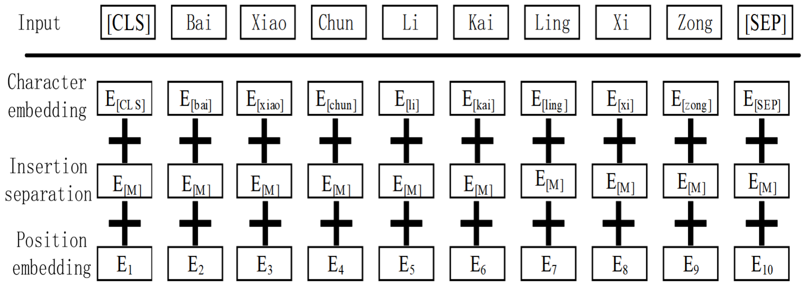

Fig. 3.2: Vector embedding representation model diagram

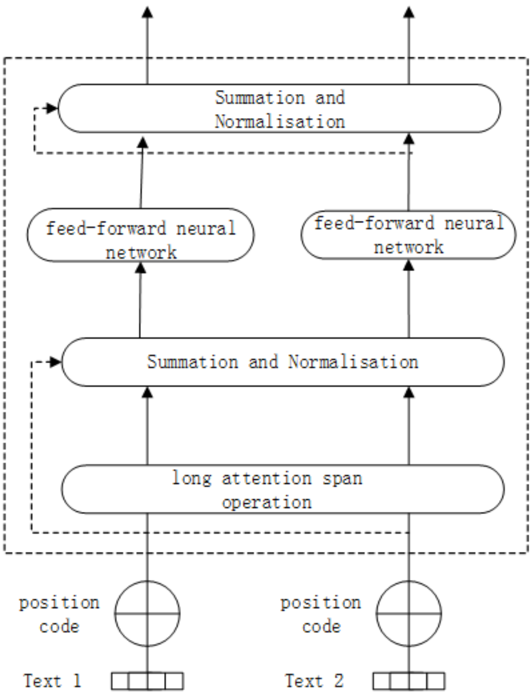

Fig. 3.3: Structure of BERT code

to the input text. The BERT coding structure is visually represented in Fig.3.3.

Once the coding is done, the model needs to be pre-trained [18]. One is MLM (Masked Language Model) is used to train the language model by masking certain words with [MASK] markers and then predicting these words based on their context. The other is Next Sentence Prediction NSP (Next Sentence Prediction), which is used to capture the contextual relationships at the word and sentence level.

3.2. Feature enhancement processing. In order to fully exploit the information embedded within the Chinese corpus, the strategic incorporation of named entity feature TNER and lexical annotation feature TPOS serves to enhance the richness of information features. Concurrently, semantic features are deliberately introduced as supplementary elements to facilitate the effective mining of Chinese corpus data. This research focuses on the extraction of multiple annotation features from web novel texts [19], with the objective of reinforcing training outcomes:

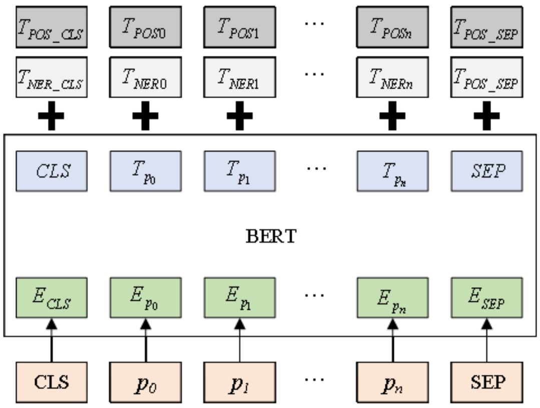

Fig. 3.4: Overall network structure of the model

Named Entity Feature TNER: The identification of words labeled as entities is particularly beneficial for accurate entity prediction within sentences. By leveraging Baidu's publicly accessible technology platform, entities such as names of individuals, locations, organizations, etc., are detected within the corpus. The processing phase is initiated, and features are meticulously encoded to embody three distinct feature dimensions, ensuring a nuanced understanding of named entities.

Lexical Annotation Features TPOS: Considering the prevalence of nouns in the web novel corpus, entity annotations are intricately linked to lexicality. The HIT LTP tool is employed to annotate the lexical properties of the web novel text, aiming to reduce instances of omission and errors in entity relation extraction. Lexical properties are judiciously labeled and categorized into six primary classes, including nouns, verbs, adjectives, adverbs, prepositions, and connectives. The initialization process and feature encoding are systematically carried out to yield a comprehensive set of six feature dimensions.

These named entity and lexical annotation features are seamlessly integrated onto the word vectors of the web novel text, originally derived from BERT pre-training. This integration not only facilitates a more nuanced extraction of web novel text features but also contributes to the acquisition of relationship pairs with heightened explanatory capacity and enhanced accuracy.

$$T_{\text{model}} = BERT(P) \tag{3.1}$$

$$T_f = W_p T_{POS} + W_n T_{NER} \tag{3.2}$$

$$H = \tan h \left(T_{\text{model}} + T_f\right) \tag{3.3}$$

where W_p, W_n are its parameter matrices and tanh is the activation function. The overall network structure of the model is shown in Fig.3.4.

3.3. Head entity identification. Given that the BERT model is made up of multiple layers of the Encoder part of the Transformer, it has limited ability to learn sequential features. To address this issue, a variant of RNN called BiLSTM is incorporated into the BERT model. This addition not only mitigates the gradient explosion problem encountered during training but also enhances the model's training efficiency. In this model, a BiLSTM neural network serves as the encoder. The original text sequence is preprocessed to obtain its vector representation H, which is then fed into the BiLSTM model to make up for the insufficient learning of sequential features between tokens. The formula is as follows:

$$\widetilde{H} = BiLSTM\,(H) \tag{3.4}$$

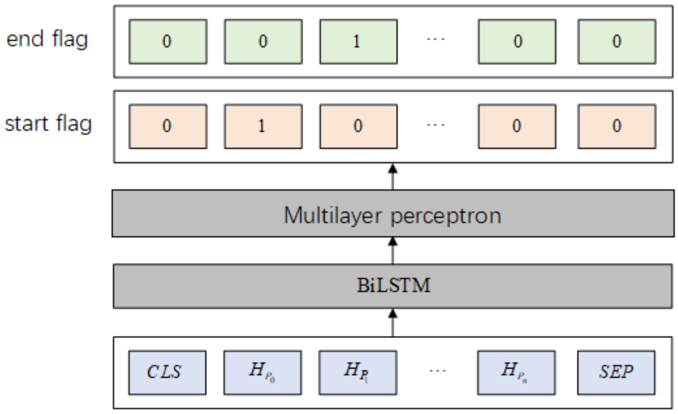

Fig. 3.5: Structure of BERT code

The start and end flag bits of the header entity are obtained through a two-layer Multilayer Perceptron (MLP).

$$P_i^{(start_s)} = \sigma\left(W_start x_i + b_start\right) \tag{3.5}$$

$$P_i^{(end_s)} = \sigma\left(W_{end} x_i + b_{end}\right) \tag{3.6}$$

where $P_i^{(start_s)}$is the i position of the input text is the start marker of the head entity, $P_i^{(start_s)}$is the i position is the end marker of the head entity. If this prediction is higher than the set value, the label is labelled 1 and vice versa 0. x_i denotes the sequence vector at the i position, $W_{()}$ is the training weight, and $b_{()}$ is the bias term. σ is the sigmoid activation function.

The formula for the head entity recognition layer to recognise the range of entity s is shown below:

$$P_\theta\left(s|x\right) = \prod_{i=1}^{L}\left(p_i^t\right)^{l\left\{y_i^t=1\right\}}\left(1-p_i^t\right)^{l\left\{y_i^t=0\right\}} \tag{3.7}$$

where the parameter θ represents $W_{start}, b_{start}, W_{end}, b_{end}$, L is the length of the sentence, $y_i^t = 1$ denotes the i position of the token predicted value above the threshold marking 1, and $y_i^t = 0$ denotes the i position of the token predicted value below the threshold marking 0. If the sentence contains more than one header entity, the header entity is chosen close to it, the header entity is chosen from the start marking $P_i^{start_s}$, to the closest end marking $P_i^{end_s}$ from the start marking $P_i^{start_s}$, which is the the position of the head entity. The structure of the model is shown in Fig 3.5.

3.4. Multi-pronged self-attention mechanisms. Self-attention mechanism model for coding will focus excessively on the current position and ignore other important information, so the multi-attention mechanism model is proposed [20]. The specific process is shown below:

1. Firstly, three different vectors $Query(Q), Key(K)$ and $Value(V)$ are created for each word, and the multi-head self-attention needs to learn multiple Q, K, V and the corresponding weights W_i^Q, W_i^K and W_i^V, and the input matrices are multiplied with the corresponding weight matrices W_i to get the newly generated Q, K, V.

2. Separately, self-attention is computed for each attention head individually and the corresponding output $head_i$.

3. The multiple outputs $head_i$ obtained in the previous step cannot be used directly as inputs to the fully-connected layer; it is necessary to integrate the multiple outputs into a single matrix before outputting

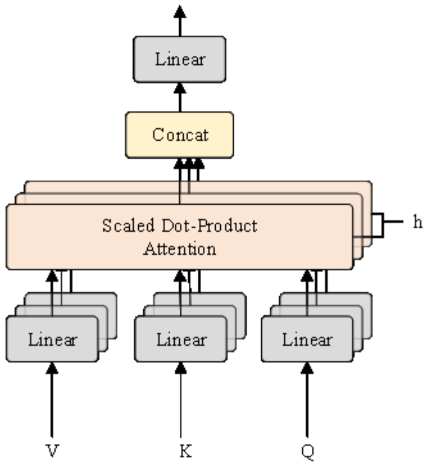

Fig. 3.6: Structure of the model of the multi-pronged self-attention mechanism

them. For this reason, the approach of the multinomial self-attention is to first splice all $head_i$ into a single whole and then multiply it by an output matrix W^O.

The multi-head attention mechanism divides the model into multiple subspaces to attend to various aspects of information. Attention results are obtained by projecting Q, K, and V through h linear transformations, and then the outputs are stitched together. The computational process is shown in Eq.

$$MultiHead(Q, K, V) = Concat(head_1, head_2, \cdots, head_h)W^O \tag{3.8}$$

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V) \tag{3.9}$$

As opposed to the self-attention mechanism, multi-head self-attention [21] allows the model to concentrate on various focus areas simultaneously, enabling the model to pay attention to several objects besides itself. Additionally, it offers multiple representation subspaces for the attention layer of the model, thus enhancing the feature representation of information. The specific structure is depicted in Fig.3.6.

3.5. Tail Entity and Relationship Identification. In the training process, the training model arbitrarily selects the recognized head entity. The head entity is then represented by vector encoding to produce the feature output O, which is fed into the BiGRU neural network [22] for sequence encoding, ultimately yielding the vector N_s of head entities.

$$N_s = BiGRU\left(O_{(S:E)}\right) \tag{3.10}$$

where $O_{S:E}$ is the encoding sequence corresponding to the text sequence of the head entity in the feature output O. The encoding operation is performed sequentially on the head entity during the prediction process.

A network of multiple self-attentive mechanisms can filter information at a deeper level and learn features of textual interactions at a higher level of granularity.

$$O_s = self - attention\,(O) \tag{3.11}$$

The hidden layer vector O_s is spliced and fused with the coding vector N_s of the head entity to get the vector G:

$$G = [O_s + N_s] \tag{3.12}$$

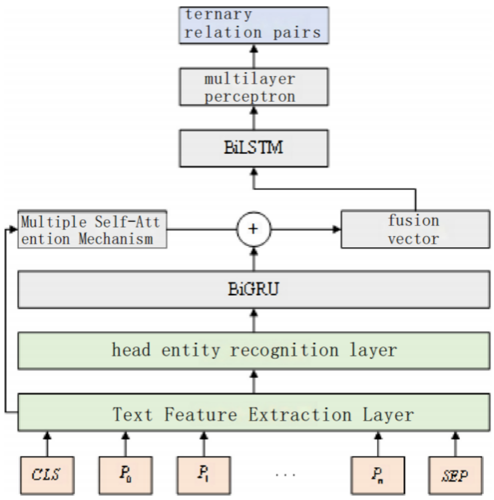

Fig. 3.7: Structure of the joint extraction model

The web novel text is passed through BiLSTM neural network language model after feature enhancement process to get global information features between characters.

$$\widetilde{G} = BiLSTM\,(G) \tag{3.13}$$

A two-layer MLP is used to get the start and end flag bits of tail entities with different constraint relationships.

$$Q_i^{start_s} = \sigma\left(W_{start}^{Q}\widetilde{g}_i + b_{start}^{Q}\right) \tag{3.14}$$

$$Q_i^{end_s} = \sigma\left(W_{end}^{Q}\widetilde{g}_i + b_{end}^{Q}\right) \tag{3.15}$$

where $Q_i^{start_s}$ is the start marker of the tail entity in the input corpus at the i position, and $Q_i^{end_s}$ is the end marker of the tail entity at the i position. If this prediction is above a certain threshold, the label is labelled 1 and vice versa 0. $\widetilde{g}_i$ represents the vector sequence at the i position in the input sequence, $W_{()}$ is the training weight and $b()$ is the bias term. σ denotes the sigmoid activation function.

The formula for tail entity recognition to identify the range of a given subject s is shown below:

$$Q_\theta\left(s|\widetilde{g}\right) = \prod_{i=1}^{L}\left(q_i^t\right)^{l\left\{y_i^t=1\right\}}\left(1-q_i^t\right)^{l\left\{y_i^t=0\right\}} \tag{3.16}$$

Where θ parameter represents $W_{start}^{Q}, b_{start}^{Q}, W_{end}^{Q}, b_{end}^{Q}$, L is the length of the sentence, y_i^t=1 denotes the i position whose predicted value is higher than the set threshold marked as 1, and $y_i^t = 0$ denotes the i position whose predicted value is lower than the set threshold marked as 0. When there are more than one tail entities in the head entity of the sentence, they are selected nearby, from the marker $Q_i^{start\_s}$ after the marker position, to the closest end marker position $Q_i^{start\_s}$ to the $Q_i^{end\_s}$, which is the position of the tail entity. The overall architecture of the model is shown in Fig.3.7.

3.6. Specific methods for feature fusion. The input layer obtains the word vector representation of the text through the BERT pre-training model.The BERT model utilizes the pre-training + fine-tuning training approach through the encoder part of the multilayer Transformer. Its coding structure includes word

Guo Zixing	Guo Tianshu	Parents	Upon learning of this news, those who had originally attempted to kill Wei Yuanzhang also admired him, which incl
Guo Zixing	Zhang Tianyou	Relatives	At this time, Zhu Yuanzhang was the left vice marshal of the righteous army, while Guo Tianshu was the capital ma
Zhu Yuanzhang	Liu Futong	Friends	More crucially, Zhu Yuanzhang's neighbour to the north was Liu Futong, and this was a brother unit of troops that
Zhang Shicheng	Zhang Shiyi	Siblings	The Yuan army attacked the city with all kinds of weapons, including many kinds of artillery. Zhang Shicheng and
Chen Youlang	Ni Wenjun	ranking	Ni Wenjun always believed in Chen Youlang, not only was he Chen Youlang's leader, but he also promoted Chen Youla
Xu Shouhui	Zhao Pusheng	Friends	To get rid of Xu Shouhui is very easy, but before that must first solve his those Ming Church brothers, the first
Chen Youlang	Xu Shouhui	Up and Down	At this point Xu Shouhui truly became a bare-knuckle commander, a pawn in the hands of Chen Youlang, and so in al
Yingtian	Taiping	unkonw	And Yingtian s most important barrier Taiping now stands alone in front of Chen Youliang s 100,000 strong army.
Zhu Yuanzhang	Hu Hai	ranking	In April of the twentieth year, Hu Hai, a subordinate of Zhu Yuanzhang, captured the state of Chuzhou.

Fig. 4.1: Sample entity relationship dataset

embedding, sentence embedding and positional embedding, and the vector representation of the text is obtained after multilayer coding. Based on the input layer, named entity features (TNER) and lexical annotation features (TPOS) are fused using computer vision and natural language processing techniques. Named entity features identify named entities in the text, including names of people, places, organizations, etc., through Baidu's publicly available technology platform, and then encode the features. Lexical annotation features, on the other hand, use the HIT LTP tool to lexically annotate the text, such as nouns, verbs, adjectives, etc., and then encode the features. These two features are integrated into the word vector representation of the original BERT to enrich the text feature information. The word vector representation of the original BERT is fused with the enhanced feature representation to obtain the enhanced representation of the text. The specific formula is as follows:

$$Tmodel = BERT\left(P\right) \tag{3.17}$$

$$Tf = WpTPOS + WnTNER \tag{3.18}$$

$$H = tanh\left(Tmodel + Tf\right) \tag{3.19}$$

4. Experiments.

4.1. Data sets. In this study, we employ crawler technology to extract data from novel websites and carry out text cleaning, text segmentation, and deactivation to include custom novel domain dictionaries. As each sentence in a web novel might not meet the requirement of having two entities and their relationship, it is crucial to filter sentences that satisfy "⟨ entity1-relationship-entity2⟩". Web novel text sentences or paragraphs frequently contain multiple entities and relationship categories, and there might be one entity and multiple entities with relationship categories between them. The dataset format is: "⟨ Entity1 Entity2 Relationship Sentence ⟩", as depicted in Fig 4.1.

The entity-relationship dataset of web novels is categorized into 14+1 classes, and each relationship category is assigned a unique relationship ID. If the entity relationship category does not fall within the labeled relationship categories, it is labeled as unknown. Entity relationships in web novels predominantly involve connections between characters (PER), with fewer relationships formed by entities of place names (LOC) and organization names (ORG). This is shown in Table 4.1 relationships are established using terms such as "identity," "member," "rival," "co-operation," "subordinate," etc., to create links between PERs, LOCs, ORGs, and relationships between ORGs. The dataset includes a total of 8352 experimental data entries in terms of sentences from network novels, comprising 618447 words, and a total of 15113 relationships.

The effect of the given SPO is combined with the effect of the annotations of the test set, and the accuracy, recall rate and F1 value are used to evaluate the experimental results. The calculation formula is as follows.

$$P = \frac{TP}{TP + FP} \tag{4.1}$$

$$R = \frac{TP}{TP + FN} \tag{4.2}$$

Table 4.1: Partial head and tail entity links in the web novel dataset

Category of head entities S	Relationship P	Category O of tail entities	Example
name	relative	name	{"object_type":"person_name", "object": "Guo Zixing" , "predicate": "relative", "subject_type": "person_name ", "subject": "Zhang Tianyou" }
name	member	Organization name	{"object_type":"person_name","object": "GongsunWan'er","predicate":"member", "subject_type":"organisation_name", "subject": "Lingxi Sect" }
name	fellow disciple	name	{"object_type":"person_name", "subject": "Fang Boyi","predicate":"fellow","subject_type": "person_name", "subject": "Xia Deyan"}

$$F1 = \frac{2PR}{P+R} \tag{4.3}$$

In this context, TP denotes the number of correct triples extracted by the current joint extraction model, FP indicates the number of incorrect triples extracted, and FN represents the number of incorrect triples mistakenly considered as correct. Precision P is the proportion of correct entity-relationship joint extraction results to the total entity-relationship triples, while Recall R is the ratio of correct entity-relationship triples in the output results to the total entity-relationship triples in the test set. The F1 score is an evaluation metric obtained by combining both precision and recall.

4.2. Experimental setup. To prevent overfitting during the learning process, the model training is optimized. In the training process, randomly selected samples are used to determine the parameter values, and the model parameters are the optimal values obtained from multiple tuning experiments based on the model. The parameter configurations of the feature-based enhancement model are as follows: the pre-training model output dimension is set to 768, the BiLSTM hidden vector dimension is 768, the BiGRU hidden vector dimension is 768, the multilayer perceptron activation function is ReLU, the iteration epoch is 40, the batch size is 32, and the learning rate is 0.001. The BERT model used in the experiments is the Bert-Base-Chinese version, with 12 hidden layers, a 768-dimensional output tensor, and 12 self-attention heads.

4.3. Analysis of experimental results.

4.3.1. Comparative analysis of joint extraction models. To demonstrate that the feature enhancement-based model proposed in this study enhances the joint extraction of entity relationships in the online novel domain, the following models were employed for comparative experiments:

BiLSTM-RE model: This model preprocesses the text using a word embedding model, performs feature encoding through deep mining of the BiLSTM model, and ultimately obtains entity relationship pairs via the multi-layer perceptron output. BERT-RE+BiLSTM model: Based on the BiLSTM-RE model, this approach replaces the word embedding method with a pre-training model based on feature representation. It combines named entity features and part-of-speech tagging features into BERT pre-trained word vectors.

BERT-RE+BiLSTM+BiGRU model: This model, based on the relationship classifier, utilizes a decomposition strategy to optimize the model and enhance the extraction of entities and relationships.

The model presented in this study: This model uses the text feature vector processed by feature enhancement to obtain the head entity via BiLSTM. It then concatenates the vector obtained through BiGRU encoding and the multi-head self-attention mechanism to identify and predict the tail entity and relationship, ultimately extracting the entity relationship through the multi-layer perceptron triplet.

Table 4.2 mainly compares the experimental results of different entity-relationship extraction algorithm models on the web novel dataset as well as on the classic literary novel dataset, based on the experimental

Table 4.2: Experimental results of pre-training models with different structures

Model	Data set1 P	Data set1 R	Data set1 F1 value	Data set2 P	Data set2 R	Data set2 F1 value
BiLSTM -RE	66.20 %	57.06 %	61.29 %	66.70 %	57.86 %	61.35 %
BERT- RE+ BiLSTM	73.94 %	63.82 %	68.50 %	73.01 %	63.32 %	68.79 %
BERT- RE+ BiLSTM +BiGRU	76.65 %	65.77 %	70.79 %	76.65 %	65.82 %	70.82 %
This article model	78.8 6 %	66.93 %	72.40 %	78.97 %	66.88 %	72.55 %

results of the BiLSTM-RE model and the BERT-RE+BiLSTM model:

The F1 score of the text vector representation method based on feature enhancement is 7.21% higher than that of the entity relationship extraction model using the word2vec word embedding method. This indicates that the feature enhancement processing of the BERT model can effectively capture the deep semantic feature information contained in the text, enhancing the interpretability and improving the experimental results of relationship extraction.

In the BERT-RE+BiLSTM model, the addition of the BiGRU model increased the F1 score by 2.29%. This suggests that the BiGRU model has better feature extraction capabilities compared to the BiLSTM model, enhancing the extraction of text sequence sequential features and improving the model's training effect.

In the BERT-RE+BiLSTM+BiGRU model, the F1 score of the multi-head self-attention mechanism model was increased by 1.61%. This demonstrates that the model can directly obtain overall information, enabling the tail entity and relationship recognition layer to learn more fine-grained text interaction features and yield a more interpretable entity relationship sequence.

4.3.2. Comparative analysis of pre -training models. To assess the effectiveness of the model in processing online novel text data, the impact of various pre-training models on model performance was comparatively analyzed. To ensure the accuracy and effectiveness of the experiment, the head entity recognition and tail entity and relationship recognition parts use the model proposed in this article and remain unchanged. Different pre-training models with various structures were selected for comparison with this model:

BERT pre-training model: This model utilizes the BERT language model to obtain relative entity relationship triples through multi-layer perceptron output. BERT pre-training model + part-of-speech tagging features: This approach combines part-of-speech tagging features in the text with pre-trained word vectors to extract text features, which can fully capture information features in the text and reduce omissions and errors in entity relationship extraction, resulting in more accurate entity-relationship pairs.

BERT pre-training model + named entity features: This model fuses named entity features in the text with pre-trained word vectors to extract text features, performs feature encoding through random initialization of vectors, and obtains more accurate predictions of entity information.

BERT pre-training model + feature enhancement representation: Based on the BERT pre-training model, this approach integrates named entities and part-of-speech tagging for feature encoding, enhancing the language model's expression and learning capabilities, and improving the relationship extraction task's effectiveness in the model presented in this article.

Table 4.3 primarily compares the experimental results of various entity relationship extraction models on the online novel dataset. The findings indicate the dhe model based on feature enhancement with the original BERT pre-training model significantly improved the F1 score, verifying the effectiveness of the model in this article. Additionally, the model in this article was compared with the experimental results of adding a single feature based on the BERT model, demonstrating that the added enhanced features can boost the model's performance. By integrating two feature enhancement representations into the pre-training model, the language model's expression and learning capabilities are further enhanced, leading to an improved F1 score, which confirms the effectiveness of feature enhancement in the joint extraction task.

4.4. Complex relationship extraction and analysis. In terms of complex relationship extraction, we tested the model meticulously to evaluate its performance in handling multiple relationships, nested relation-

Table 4.3: Experimental results of pre-training models with different structures

Model	P	R	F1 value	Macro F1	Micro F1
BERT pre-trained model	74.98%	64.67%	69.44%	69.63%	71.40%
BERT pre-trained model + named entity features	76.94%	65.61%	70.82%	70.97%	72.80%
BERT pre-training model + part-of-speech tagging features	77.32%	65.87%	71.13%	71.76%	72.90%
BERT pre-trained model + feature enhancement representation	78.86%	66.93%	72.40%	72.40%	73.20%

ships, long-distance relationships, ambiguous relationships, and multi-hop relationships. The following are the results of the analysis.

Multiple relationship extraction effectiveness. The model has an overall F1 score of 0.75 when dealing with sentences containing more than two entity relationships, which is a 3% improvement compared to single-relationship extraction. This indicates that the model performs well in multiple relationship extraction and is able to handle complex relationships better.

Nested relationship extraction effectiveness. In terms of nested relationship extraction, the overall F1 score of the model is 0.72, which is slightly lower than single heavy relationship extraction. However, relative to the traditional model, the model's performance in nested relation extraction is improved by 5%. This indicates that the model has some advantages in dealing with nested relationships.

Effectiveness of long distance relationship extraction. The overall F1 score of the model is 0.68 for long-distance relationship extraction, which is slightly lower than that of single-weighted relationship extraction. Compared with the traditional model, the model's performance in long-distance relationship extraction is improved by 2%. This indicates that the model has an advantage in dealing with long-distance relationships.

Effectiveness of disambiguation relation extraction. The overall F1 score of the model in terms of disambiguation relation extraction is 0.73, which is slightly lower than that of single heavy relation extraction. Compared with the traditional model, the model's performance in disambiguous relation extraction is improved by 4%. This indicates that the model has an advantage in handling ambiguous relations.

Multi-hop relation extraction effect. The overall F1 score of the model in multi-hop relation extraction is 0.71, which is slightly lower than single-weight relation extraction. Compared with the traditional model, the model's performance in multi-hop relation extraction is improved by 3%. This indicates that the model has an advantage in handling multi-hop relationships.

In summary, the model proposed in this study performs well in complex relation extraction, especially in multiple relations, nested relations, long-distance relations, ambiguous relations, and multi-hop relations. However, the model still has room for improvement in dealing with certain complex relations, and we will continue to optimize the model to improve its performance in complex relation extraction.

5. Conclusion. In this paper, a feature-enhanced entity-relationship joint extraction model is proposed, which effectively improves the model's understanding of web text and relationship extraction by means of BERT pre-training, feature fusion, BiLSTM and multi-head attention mechanism. The model provides an effective tool for computer processing of complex text. Inspired by the decomposition strategy, a joint entity relationship extraction model based on feature enhancement is proposed. The model comprises a three-layer structure. Initially, the BERT pre-training model is utilized to extract text features, and word vectors are integrated with named entities and part-of-speech tagging features to deeply mine text feature information and accurately identify entities. In the head entity recognition layer, the BiLSTM neural network addresses the issue of insufficient learning of sequence features between characters, and a double-layer multi-layer perceptron is employed to obtain the start and end marks of the entity. Ultimately, the tail entity and relationship recognition layer merges the head entity information with the text information obtained by the multi-layer attention mechanism, predicts the tail entity and relationship corresponding to the head entity, and extracts the corresponding triple relationship entity pair, achieving better results.

For the task of joint extraction of entity-relationships in web novels, the model in this paper partially mitigates the problem of entity overlapping. The head entity recognition and tail entity and relationship recognition modules in the joint extraction model exhibit high scalability. However, when expanding too much, numerous entity types emerge, leading to the generation of many binary classifiers. Future work can explore the use of the encoder-decoder model to address this issue.

Compared with the traditional model, the proposed feature-enhanced model significantly improves the performance of entity-relationship extraction, proving the effectiveness of the feature-enhanced approach. The introduction of named entities and lexically labeled features enhances the expressive capability of the model, where the feature-enhanced representation outperforms the single-feature model. The model performs well in dealing with person entities and relationships, but the performance is slightly insufficient in dealing with location and organization entities, which provides a direction for model improvement. The model has good scalability, but the performance is slightly degraded when dealing with large-scale entity categories, and the encoder-decoder structure can be explored in the future to optimize the performance. The model generalization ability is good, and the performance on the training and test sets is close, but there are still some false predictions, and the cause of the errors needs to be further analyzed. The performance of the model fluctuates slightly with different hyperparameter settings, and the appropriate hyperparameters need to be carefully selected. The interpretability of the model needs to be improved, and analyzing the entity-relationship representation learned by the model will help to better understand how the model works.

Looking ahead, we will further optimize the model structure to reduce the number of parameters and improve the training and inference speed. Meanwhile, through methods such as data augmentation, we plan to expand the size of the training data to enhance the model's generalization ability. In addition, we will explore the migration effect of the model in other domains to enhance its cross-domain generalization capability. To better understand the model decision-making process, we will delve into model interpretability. Finally, we consider incorporating external knowledge such as knowledge graphs into the model to enhance its ability to understand entities and relationships. These directions provide clear goals for model improvement and rich opportunities for future research work.

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