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Unveiling the Railway Traffic Knowledge in Tibet: An Advanced Model for Relational Triplet Extraction

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Abstract: To address the deficiency of existing relation extraction models in effectively extracting relational triplets pertaining to railway traffic knowledge in Tibet, this paper constructs a Tibet Railway Traffic text dataset and provides an enhanced relation extraction model. The proposed model incorporates subject feature enhancement and relational attention mechanisms. It leverages a pre-trained model as the embedding layer to obtain vector representations of text. Subsequently, the subject is extracted and its semantic information is augmented using an LSTM neural network. Furthermore, during object extraction, the multi-head attention mechanism enables the model to prioritize relations associated with the aforementioned features. Finally, objects are extracted based on the subjects and relations. The proposed method has been comprehensively evaluated on multiple datasets, including the Tibet Railway Traffic text dataset and two public datasets. The results on the Tibet dataset achieves an F1-score of 93.3%, surpassing the baseline model CasRel by 0.8%, indicating a superior applicability of the proposed model. On the other hand, the model achieves F1-scores of 91.1% and 92.6% on two public datasets, NYT and WebNLG, respectively, outperforming the baseline CasRel by 1.5% and 0.8%, which highlights the good generalization ability of the proposed model.

Keywords: relation extraction; subject feature; attention mechanism; railway traffic in Tibet

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1. Introduction

As the highest average altitude region in the world, the construction of railways in Tibet differs significantly from that in plain areas. In recent years, the application of knowledge graph technology has emerged as a new research direction, particularly in constructing domain-specific knowledge graphs. By constructing a knowledge graph for railway traffic in Tibet, we can gain a deeper understanding of the railway development situation in this region. A knowledge graph typically comprises various relational triplets in the form of (subject, relation, object), with both the 'subject' and 'object' representing entities. These relational triplets are obtained through the task of relational extraction.

Relation extraction aims to extract potential relational triplets from textual data. The early methods generally adopt a pipeline model, which usually divides the extraction task into two subtasks: entity recognition and relation classification. Initially, potential entities within the text are identified to form entity pairs. Relation labels are then assigned to each entity pair through classification techniques. However, this model often exhibits three main limitations: 1) Error propagation: Errors generated during the entity extraction process tend to propagate and become more significant during the relation extraction phase [1]. 2) Lack of interaction between subtasks: The extraction of entities and relations is treated 32 as two independent components, overlooking the association between these subtasks [2]. 3) Presence of redundant entity pairs: In the entity extraction process, all entities in the text are extracted and paired, including those that might not be relevant. As a result, the relations between unrelated entities also require judgment, impacting efficiency [3].

In recent years, joint extraction models have partially overcome these limitations by employing a unified modeling approach for entity relation extraction. A cascaded end-to-end model, i.e., CasRel, proposed by Wei et al. (2020), has demonstrated significant improvements compared to previous pipelined models. In CasRel, relations are considered as functions that map subjects to objects, rather than being independent of entities. Consequently, the subject is extracted first, followed by the judgment of corresponding objects under each relation. However, the subject is extracted through two dense layers in CasRel, and its features are fused with the text. The fusion results are then directly used for subsequent object and relation extraction. Unfortunately, if the extraction of subject features is not accurate enough, it can lead to error propagation, thereby affecting the overall model performance. Furthermore, while CasRel has achieved promising results through training on general field datasets such as NYT and WebNLG, the availability of textual data specifically related to railway traffic knowledge in Tibet is severely limited. The scarcity of data hinders the adequate training of the CasRel model and poses challenges in adapting it to the specific context of Tibet's railway transportation.

To address the issue of error propagation impacting model performance and the limitation of insufficient training data for CasRel, this paper proposes the Subject Features and Relational Attention-enhanced Relation Extraction (SFRARE) model. Our argument is that enhancing the semantic features of the subject can alleviate error propagation caused by inaccurate identification of subject features. Additionally, enhancing the model's attention towards relations allows the model to focus more on relations relevant to the subject, reducing interference from irrelevant relations. As a result, the proposed model achieves better training performance even with limited datasets. The main contribution of this paper is as follows:

1. We construct a small-scale Chinese dataset specifically focused on Tibet's railway traffic texts, which has been manually annotated to ensure its suitability for training relation extraction models.
2. In this paper, we propose a relation extraction model (SFRARE) that enhances subject features and relational attention. The model relies on Long Short Term Memory (LSTM) to enhance subject features and mitigate the effects of error propagation. Furthermore, we incorporate a multi-head attention mechanism to enable the fusion of relation-focused attention with the text vector. This allows the model to prioritize relations that are closely related to the subject.
3. We evaluated SFRARE on the Tibet Railway Traffic text dataset and achieved a F1-score of 93.3%, which is 0.8% higher than the baseline model CasRel. To further assess the generalization ability of our model, we evaluated SFRARE on two widely-used English public datasets, namely NYT and WebNLG. The experimental results demonstrated that SFRARE outperforms mainstream models in terms of extraction performance.

2. Related Work

Knowledge graphs can be classified into two categories: general knowledge graphs and field knowledge graphs, depending on the breadth of knowledge they encompass. Field knowledge graphs, although narrower in scope, are more specialized and applicable to specific domains. The Tibet Railway Traffic Knowledge Graph that we intend to construct falls under the category of a Field Knowledge Graph. Our objective is to extract relational triplets containing relevant knowledge from textual data pertaining to Tibet Railway Traffic. In this regard, Zhang's research [4] provides a comprehensive account of the history of railway construction in Tibet, while Rong's analysis [5] delves into the role of the Qinghai-Tibet railway in shaping the spatio-temporal structure of transportation in Tibet. These research works serve as valuable resources for us to accumulate the necessary knowledge about railway traffic in Tibet, thereby facilitating our search for pertinent specialized texts.

Using a relation extraction model, it is possible to extract relational triplets containing field-specific knowledge from specialized textual data in the field. Early models for relational extraction typically employed a pipelined approach, which involved dividing the extraction process into two subtasks: named entity recognition and relation classification. However, this pipelined approach suffers from

doi:10.20944/preprints202309.1397.v1

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error propagation and a lack of interaction between the subtasks, leading to underutilization of information. In recent years, there has been a growing research trend towards joint extraction of entities and relations, which has shown improved model performance. This approach involves establishing a unified model that allows different subtasks to interact with each other, resulting in better overall performance [6]. Neural network-based joint entity-relation extraction has become the mainstream in research due to the excellent feature learning ability of neural networks. These models can be categorized into joint decoding based methods and shared parameter based methods, depending on the type of decoder used.

Joint extraction models based on shared parameters decompose joint extraction into different subtasks, where information is shared at the sequence coding layer. The SPTree model [7] was the first neural network-based joint extraction model for entities and relations. Tan et al. [8] and Liu et al. [9] proposed models that utilize Conditional Random Field (CRF) at the sequence coding layer to enhance entity recognition accuracy. The RIN (recurrent interaction network) model [10] employs bi-directional LSTM to capture dynamic interaction information at the shared parameter layer. Wei et al. took a novel perspective on Relation Extraction, defining relation as a function mapping the subject to the object. They introduced the cascading relation extraction framework called CasRel [11] for extracting relational triplets. Wang et al. [12] proposed a joint extraction model that achieves entity and relation extraction through a Handshaking Tagging method. Another model by Wang et al. [13] incorporates two encoders to separately encode entity information and relation type information, enabling internal interaction between them.

On the other hand, joint decoding based extraction models typically employ a unified decoder that is superimposed on the sequence coding layer. This decoder directly decodes the relational triplet information from the encoded sentence sequences. Zheng et al. [14] proposed a model that utilizes sequence annotation to achieve joint extraction for the first time. The model directly decodes the encoded sentence sequences to obtain sequence labeling information, which is then used to derive the relational triplets. Building upon Zheng's work, Dai et al. [15] address the issue of overlapping relationships by incorporating a position-based attention approach and CRF to generate distinct sequence annotations. SPN (set prediction network) [16] employs a non-autoregressive decoder based on Transformer [17]. It also introduces an ensemble-based bisection matching loss function, enabling the generation of an ensemble containing all relational triplets simultaneously.

In general, the work by Zhang and Rong has significantly contributed to our understanding of railway traffic in Tibet. Their research has provided us with a more comprehensive knowledge base, enabling us to search for relevant textual data as better references. Additionally, the joint extraction model enhances the interaction between subtasks by constructing a unified model that fully leverages the information from each subtask. This approach presents a novel idea for extracting relational triplets. The CasRel model, in partic ular, considers relations as functions that map subjects to objects, challenging the traditional notion of separating relations from entity pairs. This method of extracting relational triplets serves as an inspiration for the development of the SFRARE model proposed in this paper.

3. The SFRARE Model

3.1. Relational triplet representation

Relational triplets can be used to represent relations between entities. The relational triplets present in the text can be obtained through the relation extraction task, as shown in Figure 1:
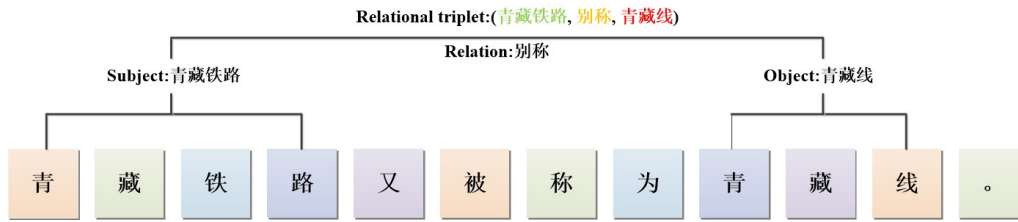
Figure 1. There exists a relational triplet (青藏铁路 (Qinghai-Tibet Railway), 别称 (alternative name), 青藏线 (Qinghai-Tibet Line)) in this example sentence. The subject of this triplet is 'Qinghai-Tibet Railway', the object is 'Qinghai-Tibet Line' and the relation between them is 'alternative name'. This relational triplet represents the information that the alternative name of 'Qinghai-Tibet Railway' is 'Qinghai-Tibet Line'.

3.2. Overall framework of SFRARE model

SFRARE is a cascading end-to-end relation extraction model proposed in this paper. It consists of 5 key components, including a text embedding layer, a subject recognizer, a subject features enhancement module, a relational attention enhancement module, and a relation-object recognizer. The structure of the SFRARE model can be visualized in Figure 2.
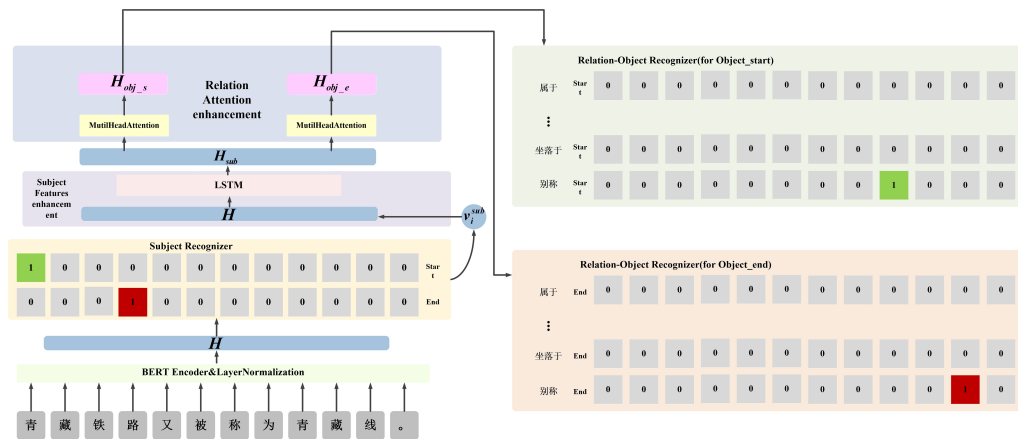
Figure 2. The BERT embedding layer and normalization layer receive the input text depicted in Figure 2. The output of this process is the text vector denoted as H. The subject recognizer identifies and extracts the subject from the text, while also marking the start and end positions of the subject as 1. In this case, the extracted subject is ' 青藏铁路 (Qinghai-Tibet Railway)'. The subject features enhancement module takes the text vector H as input, which incorporates the subject features v_i^{sub}. The output of this module is the enhanced text vector H_{sub}. The relational attention enhancement module receives the enhanced text vector H_{sub} as input. It produces two text vectors with relational attention, namely H_{obj_s} and H_{obj_e}, as outputs. The relation-object recognizer takes the two text vectors with relational attention (H_{obj_s} and H_{obj_e}) as inputs. It extracts the start and end positions of the object. In this case, the extracted object is ' 青藏线 (Qinghai-Tibet Line)'corresponding to ' 青藏铁路 (Qinghai-Tibet Railway)'under the relation ' 别称 (alternative name)', thereby forming a relational triplet (' 青藏铁路 (Qinghai-Tibet Railway)', ' 别称 (alternative name)', ' 青藏线 (Qinghai-Tibet Line)').

3.3. Text Embedding Layer

The BERT pre-trained model [18] is employed as the text embedding layer due to its ability to incorporate contextual information and learn deep word representations. This model has demonstrated excellent performance in various natural language processing tasks since it was proposed. To facilitate convergence and mitigate issues such as gradient explosion or vanishing, a normalization layer

is employed to process the vector representation of the text. This process can be represented by Equation (1):

$$H = Normalize(BERT(X)) \tag{1}$$

where $X = x_1, x_2, ..., x_n$ represents the word sequence of the text. Each x_i represents a word that constitutes the text, and n represents the total number of words in the text. *Normalize* denotes the normalization layer, and H represents the resulting text vector representation obtained after passing the input text through the pre-trained model embedding and normalization layer processing. The dimension of H is $b \times l \times d$, where b represents the batch-size or the amount of data in one training iteration, l represents the length of the text, and d represents the dimension of the output from the last hidden layer of the pre-trained model.

3.4. Subject Recognizer

The subject recognizer is employed to extract potential subjects from the text. It takes the vector representation of the text after BERT embedding as input. The recognizer treats subject extraction as a binary classification task and utilizes two binary classifiers to label each word in the text. These classifiers determine whether a word is the head or tail of a subject. If a word is identified as the head or tail of a subject, it is marked as 1; otherwise, it is marked as 0. The specific details are illustrated in Equations (2) to (3):

$$p_i^{sub_s} = Sigmoid(W_{sub_s}h_i + b_{sub_s}) \tag{2}$$

$$p_i^{sub_e} = Sigmoid(W_{sub_e}h_i + b_{sub_e}) \tag{3}$$

where $p_i^{sub_s}$ and $p_i^{sub_e}$ represent the probabilities of each word in the text being the start and end of the subject, respectively. W_{sub_s} denotes the weight matrix used for determining the start of the subject, and b_{sub_s} is the corresponding bias term. Similarly, W_{sub_e} represents the weight matrix used for determining the end of the subject, and b_{sub_e} is its corresponding bias term. h_i represents the vector representation of each word in the text.

3.5. Subject Features Enhancement Module

To mitigate the influence of error propagation on the model's extraction performance caused by inaccurate subject feature recognition, we developed the subject features enhancement module. This module combines the text vectors with the subject features identified by the subject recognizer to generate new vectors. Subsequently, the LSTM neural network evaluates the semantic features embedded in these fused vectors. The process is demonstrated in Equations (4) to (5):

$$H_{sub} = H + v_i^{sub} \tag{4}$$

$$H_{sub} = LSTM(H_{sub} + b) \tag{5}$$

where H represents the text vector representation, H_{sub} represents the updated text vector representation obtained after subject feature fusion and enhancement. v_i^{sub} denotes the feature vector of the subject, and b represents the bias term of the LSTM neural network. The enhancement of subject semantic features enriches the vector representation by incorporating more detailed subject features and reinforcing the memory of these features. This helps mitigate the issue of error propagation resulting from inaccuracies in subject recognition.

3.6. Relational Attention Enhancement Module

To ensure that the model performs well in the relational extraction task even with limited training data, we developed the relational attention enhancement module. This module utilizes a multi-head attention mechanism to compute the weights of each relation based on the enhanced subject features and text vector representation. The attention weights assigned to each relation indicate the degree of

association with the subject. Consequently, the model can focus more on relations that are relevant to the subject. This process is illustrated in Equations (6) to (9):

$$head_{s_i} = softmax(\frac{Q_{obj_s}K_{obj_s}^T}{\sqrt{d_k}})V_{obj_s} \tag{6}$$

$$H_{obj\_s} = Concat(head_{s_1}, head_{s_2}, ..., head_{s_m})W \tag{7}$$

$$head_{e_i} = softmax(\frac{Q_{obj_e}K_{obj_e}^T}{\sqrt{d_k}})V_{obj_e} \tag{8}$$

$$H_{obj\_e} = Concat(head_{e_1}, head_{e_2}, ..., head_{e_m})W \tag{9}$$

where Q_{obj_s}, K_{obj_s}, and V_{obj_s} are obtained through linear transformations of the text vector representation enhanced by the semantic features of the subject. The $head_{s_i}$ represents the attention weights assigned to each relation for recognizing the start of the object, while $head_{e_i}$ represent the attention weights assigned to each relation for recognizing the end of the object. W is the output matrix. H_{obj_s} and H_{obj_e} are the text vector representations obtained after merging the relational attention. These representations are then utilized for the recognition of the start and end of the object, respectively.

3.7. Relation-object Recognizer

The relation-object recognizer is employed to extract the object that corresponds to the subject under a given relation. Similar to the subject recognizer, the object recognizer utilizes two binary classifiers for each relation. These classifiers determine whether each word in the text represents the start or end of the object corresponding to the subject under the current relation. The process is demonstrated in Equations (10) to (11):

$$p_i^{obj_s} = Sigmoid(W_{obj_s}^r h_{i_s} + b_{obj_s}^r) \tag{10}$$

$$p_i^{obj_e} = Sigmoid(W_{obj_e}^r h_{i_e} + b_{obj_e}^r) \tag{11}$$

where $p_i^{obj_s}$ and $p_i^{obj_e}$ represent the probabilities of each word in the text being the start and end of the object, respectively. These probabilities are calculated similarly to equations (2)-(3). $W_{obj_s}^r$ represents the weight matrix used for determining the start of the object under relation r, while $W_{obj_e}^r$ represents the weight matrix used for determining the end of the object under relation r. The terms $b_{obj_s}^r$ and $b_{obj_e}^r$ denote the corresponding bias terms. The vectors $h_{i_s} \in H_{obj\_s}$ and $h_{i_s} \in H_{obj\_e}$ are obtained from the relational attention enhancement module and are utilized for recognizing the start and end of the object, respectively.

3.8. Loss Function

In the SFRARE model, the extraction of both the subject and the object are treated as binary classification labeling tasks. Therefore, the binary cross-entropy loss function is employed. Since the model first extracts the subject and then proceeds to extract the corresponding object under the given relation, the losses during the extraction process are calculated separately and subsequently summed. The specific calculations are outlined in Equations (12) to (14):

$$l_s ub = \sum_{j \in \{sub_s, sub_e\}} (-\frac{1}{L}\sum_{i=1}^{L}(y_i^j ln p_i^j + (1 - y_i^j)ln(1 - p_i^j)) \tag{12}$$

$$l_o bj = \sum_{j \in \{obj_s, obj_e\}} (-\frac{1}{L} \sum_{i=1}^{L} (y_i^j ln p_i^j + (1 - y_i^j) ln(1 - p_i^j)) \tag{13}$$

$$Loss = l_s ub + l_o bj \tag{14}$$

where $l_s ub$ represents the loss incurred during the subject extraction, $l_o bj$ represents the loss incurred during the object extraction, and *Loss* represents the overall loss of the entire model. *L* denotes the length of the text. The variables y_i^j represent the ground truth start and end positions of the subject and object, as indicated in equations (12) and (13). On the other hand, p_i^j represents the predicted start and end positions of the subject and object made by the model.

4. Experiments

4.1. Tibet Railway Traffic text Dataset

Due to the unavailability of a publicly accessible text dataset specifically focused on railway traffic in Tibet, we borrow ideas from Zhang and Rong's works. Specifically, we utilized the history of railway construction in Tibet as an index to gather relevant textual data from the internet. For instance, we extracted texts containing knowledge related to railway traffic from the introduction of Qinghai-Tibet Railway on Baidu Baike (a Chinese online encyclopedia). Subsequently, we manually annotated the relational triplets present in these texts. These annotated textual data were then utilized to train our model, as illustrated in Figure 3.

{"text":"青藏铁路简称青藏线，是通往西藏腹地的第一条铁路，也是世界上海拔最高、线路最长的高原铁路。","spo_list":[{"subject":" 青藏铁路","relation":"别称","object":"青藏线"}]}

Figure 3. Each piece of textual data is stored as a dictionary. The key 'text' represents the text itself, and its corresponding value is the textual data that has been collected. The key 'spo_list' represents the set of relational triplets present in the text, and the corresponding value is a list that records the relational triplets. Each relational triplet is stored as a dictionary within this list. Finally, all the annotated textual data is stored as a dataset in a JSON-formatted file.

In addition, we conducted searches using each railway station in Tibet as the departure and arrival stations to find train numbers. We then utilized the relevant information associated with these train numbers to create textual data. This portion of the text was also manually annotated with relational triplets for training the model in relation extraction tasks. We collected a total of 2056 textual data samples related to railway traffic in Tibet. These samples were used to construct a small Chinese text dataset specifically for the task of relation extraction in Tibet's railway traffic domain. The constructed dataset was further divided into train set, validation set, and test set, with a ratio of 8:1:1 respectively. Details of the dataset division are presented in Table 1.

Table 1. Data Statistics for Tibet Railway Traffic text Dataset.

Dataset	Train	Valid	Test	ALL
Tibet Railway Traffic text Dataset	1645	205	206	2056

Through the exploration of railway traffic knowledge in Tibet, we have identified a total of 16 types of relations. These relation types were defined in Chinese originally, and the translation in English is shown in Table 2.

Table 2. Relation types of Tibet Railway Traffic text Dataset.

Relation Type	The number of triplets	Relation Type	The number of triplets
railway station-**be located in**-location	205	railway station-**cover an area of**-area	163
railway-**alternative name**-name	23	railway-**construction date**-date	35
railway-**finish date**-date	63	railway-**opening date**-date	32
railway-**length of railway**-length	22	railway-**width of railway**-width	17
railway-**height of railway**-elevation	26	railway-**belong to**-railway	46
train-**departure station**-railway station	54	train-**terminal station**-railway station	54
train-**departure time**-time	54	train-**journey time**-time	54
constructors-**construct**-railway	468	passenger-**take the train**-train	762
The number of all triplets		2078	

As depicted in Table 2, we have defined 16 relation types for the dataset that we constructed. The table displays the format of the relational triplets formed by each relation type, along with their corresponding subject and object. For instance, the relation type 'railway-alternative name-name' signifies that when the subject is a railway and the object is a name, there might exist an 'alternative name' relation between them. Subsequently, we conducted a count of the number of relational triplets for each relation type and determined a total of 2078 relational triplets within the dataset.

4.2. Public Datasets

In this paper, English public datasets NYT[19] and WebNLG are used to verify the generalization ability of the proposed model. The NYT dataset is a publicly available English dataset constructed using a remote supervision method. It consists of 24 relations for relation extraction tasks. On the other hand, the WebNLG dataset was initially created for the natural language generation task but has been adapted for the relation extraction task. It contains a broader range of relation types, encompassing a total of 246 different relations. The relation types present in the two datasets are detailed in Table 3.

Table 3. Data Statistics for NYT Dataset and WebNLG Dataset

Category	NYT			WebNLG		
	Train	Valid	Test	Train	Valid	Test
All	56195	4999	5000	5019	500	703

4.3. Experimental setup

The specific experimental settings of this paper are shown in Table 4.

Table 4. Experimental details

Items	Specific setting
Word embedding layer	bert_base&bert_chinese
Recognition threshold	0.5
Hidden layer dimension of LSTM	768
Number of heads of attention mechanism	num-rels
Learning rate	1e-5
Batch-size	16
Dropout	0.2
Experimental device	NVIDIA GeForce RTX 3090(24G)

We employ the BERT model developed by Google as the word embedding layer. Specifically, for the experiment conducted on the Tibet Railway Traffic text Dataset, we utilize the bert_chinese version

of BERT. For the experiments conducted on the NYT and WebNLG datasets, we use the bert_base version of BERT. The recognition thresholds for both the subject recognizer and the relation-object recognizer are set to 0.5. The hidden layer dimension of the LSTM is set to 768. Additionally, the number of heads in the two-layer multi-head attention mechanism is set to the number of relations defined by each respective dataset. During the training process, we employed the Adam optimizer with a learning rate of 1e-5 and a batch size of 16. A dropout rate of 0.5 was applied. The experimental device used was an NVIDIA GeForce RTX 3090 graphics card with 24GB of video memory. To evaluate the extraction results, we calculated the accuracy rate, recall rate, and F1-score, as shown in Equations (15) to (17).

$$Pre = \frac{TT}{PT} \tag{15}$$

$$Rec = \frac{TT}{GT} \tag{16}$$

$$F1 = \frac{2 * (Pre * Rec)}{Pre + Rec} \tag{17}$$

where TT is the number of correct triplets predicted, PT is the number of all predicted triplets, and GT is the number of actually correct triplets.

4.4. Experimental result

4.4.1. Experimental results on Tibet Railway Traffic text Dataset

Due to the limitation of experimental equipment, we could not solve the problem that some models using bert_chinese as the word embedding layer exceeded the video memory during training. In this experimental part, we only chose the baseline model CasRel as the comparison model.

- CasRel : A novel cascade binary tagging framework for relational triplet extraction proposed by Wei et al.

The experimental results on Tibet Railway Traffic text Dataset are shown in Table 5.

Table 5. Experimental results on Xizang Railway Traffic Dataset.

Model	Tibet Railway Traffic text Dataset		
	Pre	Rec	F1
CasRel	93.1%	91.9%	92.5%
SFRARE	93.7%	93.0%	93.3%

According to the experimental results presented in Table 5, the SFRARE model achieves a higher accuracy rate compared to CasRel, with an improvement of 0.6%. This suggests that the SFRARE model mitigates the impact of error propagation to some extent in comparison to CasRel. The recall rate of SFRARE is also 1.1% higher than CasRel, indicating that SFRARE better captures more relational triples in the Tibet Railway Traffic text Dataset. This implies that SFRARE performs better on this small dataset. Lastly, the F1-score achieved by SFRARE is 0.8% higher than CasRel, further supporting the conclusion that SFRARE outperforms CasRel on the Tibet Railway Traffic text Dataset.

4.4.2. Experimental results on public datasets

To assess the generalization capability of SFRARE, this paper includes several state-of-the-art relation extraction models that have previously published experimental results on two public datasets: NYT and WebNLG. In the experimental section, CasRel is selected as the baseline model for comparison against these representative models.

- CopyR$_{OneDecoder}$[20] : An end-to-end relation extraction model with replication mechanism proposed by Zeng et al., a single decoder is used at the decoding layer.
- CopyR$_{MultiDecoder}$: An end-to-end relational extraction model with replication mechanism proposed by Zeng et al., multiple decoders are used at the decoding layer.
- GraphRel$_{1p}$[21] : The first phase of relational extraction model based on relational graph structure proposed by Tsu-Jui Fu et al.
- GraphRel$_{2p}$: The second phase of relational extraction model based on relational graph structure proposed by Tsu-Jui Fu et al.
- CopyR$_{RL}$[22] : Zeng et al. proposed an end-to-end relation extraction model based on CopyR that applies reinforcement learning to the generation of relational triplets.
- CasRel : A novel cascade binary tagging framework for relational triplet extraction proposed by Wei et al.

The experimental results on the public dataset are shown in Table 6.

Table 6. Experimental results on NYT and WebNLG

Model	NYT			WebNLG		
	Pre	Rec	F1	Pre	Rec	F1
CopyR$_{OneDecoder}$	59.4%	53.1%	56.0%	32.2%	28.9%	30.5%
CopyR$_{MultiDecoder}$	61.0%	56.6%	58.7%	37.7%	36.4%	37.1%
GraphRel$_{1p}$	62.9%	57.3%	60.0%	42.3%	39.2%	40.7%
GraphRel$_{2p}$	63.9%	60.0%	61.9%	44.7%	41.1%	42.9%
CopyR$_{RL}$	77.9%	67.2%	72.1%	63.3%	59.9%	61.6%
CasRel	89.7%	89.5%	89.6%	93.4%	90.1%	91.8%
SFRARE	90.5%	91.7%	91.1%	92.6%	92.7%	92.6%

Table 6 shows that SFRARE outperforms the baseline model on both the NYT and WebNLG datasets. On the NYT dataset, SFRARE achieves a precision rate of 90.5%, a recall rate of 91.7%, and an F1-score of 91.1%. These scores are 0.8%, 2.2%, and 1.5% higher than those of the baseline model CasRel. Similarly, on the WebNLG dataset, SFRARE achieves a precision rate of 92.6%, a recall rate of 92.7%, and an F1-score of 92.6%. Even the precision rate of SFRARE is slightly lower than that of CasRel, it improves the recall and F1-score by 2.6% and 0.8%, respectively. The experimental results demonstrate that the SFRARE model exhibits favorable generalization ability and surpasses mainstream models in terms of extraction performance.

4.4.3. Ablation experiment

To examine the influence of subject feature enhancement and relational attention enhancement on the extraction performance of the SFRARE model, we conducted ablation experiments on the NYT and WebNLG datasets. The results of these experiments are presented in Table 4. In the table, SFRARE$_{SubF}$ represents the variant of the SFRARE model that only incorporates enhanced subject features, while SFRARE$_{RelA}$ denotes the variant that solely incorporates enhanced relational attention. On the other hand, SFRARE refers to the complete model that combines both subject feature enhancement and relational attention enhancement.

Table 7. The results of the ablation experiments on NYT and WebNLG.

Methods	NYT			WebNLG		
	Pre	Rec	F1	Pre	Rec	F1
CasRel	89.7%	89.5%	89.6%	93.4%	90.1%	91.8%
SFRARE$_{SubF}$	90.1%	89.8%	89.9%	92.2%	91.8%	92.0%
SFRARE$_{RelA}$	89.9%	91.0%	90.5%	93.7%	90.7%	92.2%
SFRARE	90.5%	91.7%	91.1%	92.6%	92.7%	92.6%

The experimental results indicate that enhancing subject features leads to an increase in the F1-scores achieved by SFRARE on both datasets. Specifically, compared to the baseline model, SFRARE achieves a 0.3% and 0.2% improvement in F1-score on the two datasets, respectively. Similarly, enhancing relational attention also contributes to improved performance. In comparison to the baseline model, SFRARE demonstrates an F1-score increase of 0.9% and 0.4% on the two datasets, respectively. When both subject features and relational attention are enhanced, the overall performance improvement is even more significant. SFRARE achieves an increase of 1.5% and 0.8% in F1-score on the two datasets, respectively. The results from the ablation experiments confirm that enhancing subject features and relational attention has a positive impact on the SFRARE model.

Based on the experimental results, it can be concluded that the SFRARE model surpasses the baseline CasRel and mainstream extraction models, on both the Chinese dataset (the Tibet Railway Traffic text Dataset) and two public English datasets (NYT and WebNLG). These findings demonstrate the effectiveness and generalization capability of the SFRARE model for knowledge graph construction in the field of railway traffic in Tibet. The improved performance of the SFRARE can be attributed to several factors. Firstly, the subject features enhancement module enhances the semantic features of the subject and the input text through LSTM. This provides more accurate information to the relation-object recognizer, thereby mitigating the effects of error propagation caused by inaccurate subject feature recognition. Furthermore, the relational attention enhancement module calculates the weight of each defined relation using two multi-attention mechanisms. This approach allows the model to focus more attention on relations related to the subject, thereby improving the performance of the model in extracting relation triplets. Moreover, this attention mechanism enables the model to achieve good performance even with small training datasets. Overall, the enhancements made in the SFRARE model contribute to its superior performance in relation extraction tasks, making it a suitable choice for knowledge graph construction in the field of railway traffic in Tibet.

5. Conclusions

The experimental results obtained by the model on two public datasets, NYT and WebNLG, are also better than the mainstream relation extraction models, indicating that the model proposed in this paper has the ability to generalize. In our follow-up work, we plan to continue to search for textual data about Tibetan railway traffic knowledge to expand our dataset, and continue to optimize the SFRARE model to make it more applicable to the relational triplet extraction task.

This paper introduces the SFRARE model, a relation extraction approach that enhances subject features and relational attention. Building upon CasRel, SFRARE addresses error propagation issues by improving the extracted subject features. It also tackles the challenge of limited training data in CasRel, specifically for extracting relational triplets related to Tibetan railway traffic knowledge, by enhancing relational attention to focus on subject-related relations within the text. The experimental results on the Tibet Railway Traffic textual Dataset demonstrate that the proposed model outperforms CasRel. This indicates that the SFRARE model is better suited for extracting relational triplets in the context of Tibetan railway traffic knowledge compared to CasRel. Furthermore, the experimental results on the NYT and WebNLG public datasets exhibit superior performance compared to mainstream relation extraction models, indicating the generalization capability of the proposed model.

In future work, one important aspect will be expanding the dataset by searching for additional textual data pertaining to Tibetan railway traffic knowledge. By incorporating more diverse and comprehensive data, the dataset can provide a richer training environment for the SFRARE model. This expansion will help improve the model's performance and generalization ability. We will also continue to optimize the SFRARE model to make it more applicable to the relational triplet extraction task, e.g., by designing different architectures.

Author Contributions: Conceptualization, Weiqun Luo and Guiyuan Jiang; methodology, Weiqun Luo and Jiabao Wang; software, Jiabao Wang; investigation, Jiabao Wang and Xiangwei Yan; data curation, Jiabao Wang and Xiangwei Yan; writing—original draft preparation, Jiabao Wang; writing—review and editing, Weiqun Luo and

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