A New Entity-relation Joint Extraction Model using Reinforcement Learning and Its Application Test

Heping Peng[1], Zhong Xu[1], Wenxiong Mo[1], Yong Wang[1], Qingdan Huang[1], Chengzhu Sun[2, *] and Ting He[2]

[1]*Guangzhou Power Supply Bureau of Guangdong Power Grid Co Ltd, Guangzhou, China*

[2]*College of Computer Science and Technology, Huaqiao University, Xiamen, China*

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Abstract: Extractions of entity and relation are the key part of natural language processing and its application. The current popular entity extraction methods mainly rely on artificially formulated features and domain knowledge which cannot achieve simultaneous extraction of entities and their relations, and are largely affected by noise labeling problems. This paper proposes a new entity-relation extraction model based on reinforcement learning. This model uses the joint extraction tagging strategy in which the sentences are firstly input into a joint extractor based on the Long Short-term Memory network for prediction and subsequently the reinforcement learning algorithm is based on the Policy Gradient for the extraction training. The model is tested on a public application dataset and the experimental results show the validity of the presented joint extraction algorithm.

1 INTRODUCTION

There are currently two methods that are widely used to solve the tasks of entity and relationship extraction. The traditional pipeline method first extracts the entities and then identifies the relations between the pair of entities. These two separations make the task easy to handle and more flexible. But in fact, these two tasks have a close relationship. The entity extracts information to further help the relation extraction. The quality of the entity extraction module will affect the relation extraction module. If the extracted entity pair has no relationship, it will bring unnecessary information. Noise is generated, which increases the error rate of relation extraction (Li, 2014, Ji, 2014). Unlike the pipeline approach, the joint extraction approach aims to extract both entities and relations using only one model framework. This method can effectively extract the semantic relationship between entities from unstructured text, and can improve the pipeline-based information extraction method. However, most existing joint extraction methods are feature-based structured systems (Ren 2016, Wu 2016, He 2016), which often require complex feature engineering and, to some extent, rely on other NLP toolkits to cause errors to spread. In order to reduce manual work in feature extraction, Zheng (Zheng, 2017, Wang, 2017, Bao, 2017) proposed a hybrid neural network model to extract entities and their relations simultaneously without any manual features. Although the federated model can represent entities and relations with shared parameters in a single model, they also extract entities and relationships, respectively, and generate other information.

In this paper, the joint extraction of entities and relations of unstructured texts is studied in detail. The policy gradient reinforcement learning algorithm (Williams, 1992) and Long Short-term Memory (LSTM) (Hochreiter, 1997, Schmidhuber, 1997) are used to solve the above problems. This paper proposed the algorithm model combining reinforcement learning and deep learning to jointly extract the entities and relations of public corpus by applying the joint extraction tagging strategy. Research on deep reinforcement learning methods has been widely developed and successfully applied in fields such as text games (Pascual, 2015, Gurruchaga, 2015, Ginebra, 2015) and dialogue generation (Narasimhan, 2015, Kulkarni, 2015, Barzilay, 2015). The LSTM-based end-to-end model has been successfully applied to the named entity recognition tag task (Lample, 2016, Ballesteros,

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2016, Subramanian, 2016). The LSTM neural network model can solve the problem of long-term sequence dependence, which is very helpful for sequence modeling tasks. This paper will firstly introduce joint tagging strategy for entity and relation extraction and joint extractor based on Long Short-term Memory network and trainer based on Policy Gradient reinforcement learning algorithm. The main contributions of this paper are as follows:(1) A new model based on reinforcement learning algorithm is proposed for joint extraction of entity and relation. (2) The Policy Gradient reinforcement learning algorithm is applied to the joint extraction problem, and it can better predict the entities and their relations. The model scheme based on this paper has achieved better results than most existing pipelines, joint learning methods, and provides new ideas for future research in this field.

2 RELATED WORK

Extraction of entities and relations are two common tasks in NLP (Zou, 2014, Huang, 2014, Wang, 2014), for example in Table 1 they are very beneficial for many NLP tasks such as social media analysis tasks (Sang, 2012, Xu, 2012). These two tasks are mainly based on the pipeline method and the joint extraction method. The traditional method treats the two subtasks, Named Entity Recognition (NER) (Nadeau, 2007, Sekine, 2007) and Relation Classification (CR) (Rink, 2010, Harabagiu, 2010), into separate tasks in a pipelined manner.

Table 1: Examples for the entities and relations extraction task.

	Sentences	Entities	Relation
1	**Bill Gates** and Steve Ballmer joined forces at **Microsoft** in 1980.	Bill Gates, Microsoft	Company-Founder
2	**Bill Gates** and Paul Allen founded the predecessor of **Microsoft.**	Bill Gates, Microsoft	Company-Founder
3	**Bill Gates** was the co-founder and CEO of **Microsoft.**	Bill Gates, Microsoft	Company-Founder
4	**Bill Gates** was born in the **US**.	Bill Gates, US	PlaceofBirth

2.1 Pipeline Method

The classical NER model is a linear statistical model, such as Hidden Markov Model (HMM) (Luo, 2016, Huang, 2016, Lin, 2016) and Conditional Random Fields (CRF) (Passos, 2014, Kumar, 2014, Mccallum, 2014), whose performance depends largely on manual features of NLP tools and external knowledge resource extraction. Currently, Recurrent Neuron Network (RNN) exhibits better performance than many other neural networks in many sequence-to-sequence tasks. In the neural network architecture, NER is considered a continuous marking task. Chiu and Nichols (Chiu, 2015, Nichols, 2015) proposed a hybrid model by learning the characteristics of character and word levels. They independently code each tag on a linear layer and a log-softmax layer. Miwa and Bansal (Miwa, 2016, Bansal, 2016) proposed a coded Bi-directional Long Short-term Memory (Bi-LSTM) and a separate incremental neural network structure to jointly decode the tags.

The existing relational classification models mainly include manual feature-based methods, neural network-based methods and other valuable methods (Yu, 2014, Gormley, 2014, Dredze, 2014), Mooney and Bunescu (Bunescu, 2005, Mooney, 2005) used distant supervision methods for classification, which is supervised. The method relies heavily on high quality label data. Rink (Rink, 2010, Harabagiu, 2010) designed to extract 16 features by using a number of supervised NLP toolkits and resources (including part-of-speech tagging POS, English dictionary Word-Net, etc.). However, this approach requires a lot of work to design and extract features and is heavily dependent on other NLP tools. In recent years, neural network models have been widely used in relational classification including convolutional neural networks (Chiu, 2015, Nichols, 2015), long short-term memory networks (Ebrahimi, 2015, Dou, 2015), etc., have achieved good results. There are other valuable methods. Nguyen (Nguyen, 2009, Moschitt, 2009, Riccardi, 2009) studied the use of innovative kernels based on syntax and semantic structure. The synthetic model FCM (Yu, 2014, Gormley, 2014, Dredze, 2014) studied the representation of a substructure of an infinite word statement, and FCM can easily handle arbitrary Type input and global information.

2.2 Joint Extraction Approach

The entities and relationships extracted based on the pipeline method ignore the relationship between these two subtasks, and thus propose a joint extraction model. Li and Ji (Li, 2014, Ji, 2014) proposed a joint model that incrementally predicts entities and relationships using a structural perceptron with efficient directed search. Dan and Yih (Dan, 2007, Yih, 2007) studied the global reasoning of entity and relationship recognition through linear programming formulas. Feng and Zhang (Feng, 2017, Zhang, 2017, Hao, 2017) combined the intensive learning Q-learning algorithm with the neural network to extract entities and relationships. Kate and Mooney (Kate, 2010, Mooney, 2010) proposed a new method for joint entities and relation extraction using card pyramid parsing. Yu and Lam (Yu, 2012, Lam, 2012) jointly identify entities and extract relationships in an encyclopedia through a graphical model approach. Although these methods implement joint extraction, they cannot achieve high accuracy of entity and relationship extraction and joint extraction at the same time.

3 THE JOINT EXTRACTION OF ENTITIES AND RELATIONS USING REINFORCEMENT LEARNING

This paper treats the joint entity and relation extraction task as a Markov Decision Process (MDP) and divides a complete joint extraction procedure into two parts-joint extractor and reinforcement learning for trainer. For every sentence in a bag, a reinforcement learning episode will extract the entities and their relation. Briefly, each sentence will have its corresponding action which predicted by the joint extractor and then predict that the bag relation calculated by the proposed reward function will be compared to the truly correct bag value. Finally, the trainer which is the agent by getting rewards trains the LSTMs network until convergence. Figure 1 shows how the proposed method works.

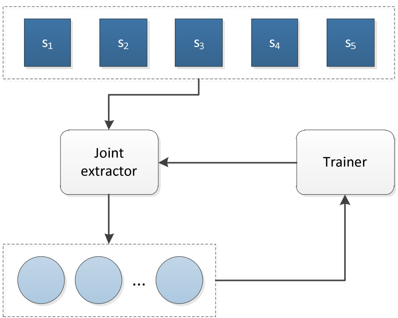

Figure 1: Overall process of this research.

3.1 Joint Extractor

This paper adopted a novel tagging scheme published in 2017 from the Association for Computational Linguistics (ACL) conference for joint extraction (Zheng, 2017, Wang, 2017, Bao, 2017). Specifically, tag "O" represents the "Other" bag; the location information of the word in the entity is marked as {B(the start of entity), I(the interior of entity), E(the end of entity), S(single entity)}; the information of relationship type{1, 2}, Where {1, 2} are respectively represented as {entity1, entity2}. This strategy combines the two subtasks in the information extraction into a sequence labeling problem to further improve the extraction task. Based on the use of a joint extraction tagging scheme, this paper only applies one LSTM network to highlight the role of reinforcement learning algorithm. The LSTM network is mainly composed of three gates: forget gate, input gate and output gate which have the ability to delete or add information to the cell state. Take the sentence "Bill Gates and Paul Allen founded the predecessor of Microsoft" as an example, where Company-Founder (CF) is the relation of Bill Gates and Microsoft. Figure 2 displays the novel strategy combined with LSTM network and LSTM memory block.

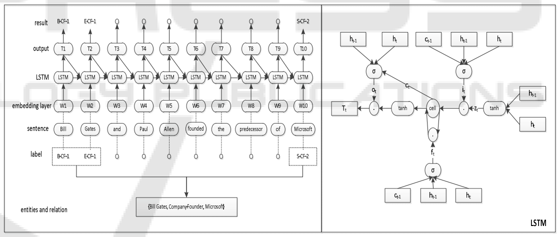

Figure 2: Example for joint extraction tagging scheme and LSTM block.

The LSTM network is a special extension of recurrent neural network to avoid long-term dependency problems. The gate structure is a way to selectively pass information, usually consisting of a sigmoid function and a point-by-point product operation (the output value of the sigmoid layer is 0 to 1, 0 and 1 respectively indicate that the information has passed and all failed). The detail operation of LSTM can be defined as follows:

$$i_t=\delta(W_{wi}h_t+W_{hi}h_{t-1}+W_{ci}c_{t-1}+b_i) \quad (1)$$

$$f_t=\delta(W_{wf}h_t+W_{hf}h_{t-1}+W_{cf}c_{t-1}+b_f) \quad (2)$$

$$z_t=tanh(W_{wc}wh_t+W_{hc}h_{t-1}+b_c) \quad (3)$$

$$c_t = f_t c_{t-1} + i_t z_t \tag{4}$$

$$o_t = \delta(W_{wo}h_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \tag{5}$$

$$h_t = o_t \tanh(c_t) \tag{6}$$

$$T_t = W_{ts}h_t + b_{ts} \tag{7}$$

Where w is the weight and b is the bias. The final softmax layer computes the confidence vector y_t^i:

$$y_t = W_y T_t + b_y \tag{8}$$

$$p_t^i(a_i|s_j,\psi)\frac{\exp(y_t^i)}{\sum_{j=1}^{N_t}\exp(y_t^j)} \tag{9}$$

Where a_i is the action predicted by the network, s_j is the representation by the joint extractor predicted and N_t is the total number of tags. In order to accelerate the training of the model and improve the accuracy of the model, this paper pre-trained the neural network and define the objective function of the joint extractor using RMSprop proposed by Hinton (Hinton 2012, Srivastava 2012, Swersky 2012) as follows:

$$J(\psi) = max \sum_{j=1}^{|S|}\sum_{t=1}^{L_j} \log(p_t^j = y_t^j|s_j,\psi) \tag{10}$$

Where $|S|$ is the size of dataset, L_j is the length of sentence s_j, y_t^j is the label of word t in the sentence s_j and p_t^i is the normalized probabilities of tags which defined in equation (9).

3.2 Reinforcement Learning for Trainer

This paper represents the MDP as a tuple (S, A, T, R), where S={s} is the collection of states, A={a} is the set of all actions, R(s) is the reward function, and $T(s^{'}|s,a)$ is the transition function. This paper introduces these definitions as follows:

States. In order to take advantage of the dataset, this paper splits the training sentences $S = \{s_1, s_2, \ldots, s_n\}$ into N bags. Define the sentence input under the current bag as state s_i in MDP.

Actions. This paper uses the policy gradient algorithm based on round update which can directly output the action value, while method based on value function can't output action values, but state-action values. Therefore, this paper will adopt the output value predicted by the LSTM network as the action in the MDP. Then according to the used tagging strategy, the total number of actions is $N_a = 2 * 4 * |R|$, where $|R|$ is the size of the predefined relation set.

Rewards. The reward function is chosen to maximize the final extraction accuracy. First, when predicting the distribution of each sentence, the predicted "O" tag is ignored. In the remaining predicted entity relationship tags, the relationship of the relationship with the largest probability value is selected as the current sentence, and then the probability value is selected by the maximum likelihood estimation. The biggest as the current bag prediction relationship, compared with the gold bag. If they are the same, the reward value of +1 for each label of the data set is given except "O", and if it is different, the reward value of -1 is given. The specific formula of the reward function is expressed as follows:

$$R(s_i|B) = \sum_{j=i}^{n}\gamma^{n-j}\,r_j = \begin{cases} \sum_{j=i}^{n}\gamma^{n-j} & r_j = 1 \\ -\sum_{j=i}^{n}\gamma^{n-j} & r_j = -1 \end{cases}$$

For example in table 1, the first three statements can be thought of as a bag. When joint extractor predicted every word's label, the label predicted is "O" like the words "and, joined, in,…" in the first sentence is ignored. And sampling the probabilities that the words "Bill", "Gates", "Microsoft" are predicted to "B-CF-1", "E-PoB-1", "S-CP-2" respectively is 0.9, 0.85, 0.7, so the maximum probability of 0.9 as the relation "Company-Founder" of the current sentence. Similarly, supposing the relations of the second sentence and the third is "Company-Founder", "PlaceofBirth". By likelihood function, the relation of this bag can be calculated as "Company-Founder". Due to the gold relation of this bag is "Company-Founder", thence the episode reward will be to set +1.

Transitions. For every episode, a sentence in a bag will be extracted and immediately next sentence will be input to joint extractor. One transition includes the agent being given the state s containing current information and the future generated. The transition function $T(s'|s,a)$ incorporates the reward value from the agent in state s and continue to choose the next state s'. The episode stops whenever the model is convergent.

Optimization. This paper uses the reinforcement learning algorithm (Williams 1992) to optimize the model. For a bag B with n sentences, the expected total reward will be maximized in the episode. The reward function of the sentence is $R(s_i|B)$, so the objective function definition is as follows:

$$J(\theta) = E_{s_1,\ldots,s_n} R(s_i|B) \quad (12)$$

According to the policy gradient algorithm (Williams 1992), this paper regards a_i as the predicted label of s_i and update the gradient θ by using the likelihood in the following way:

$$\nabla J_\theta = \sum_{i=1}^{n} \nabla p(a_i|s_i,\theta) R(s_i|B) \quad (13)$$

Algorithm 1. Presents the details of complete joint training process based on MDP framework

ALGORITHM 1: Reinforcement learning for entities and relations extraction (Training phase)
Initialize the parameters of the LSTM model of joint extractor with random weights respectively. Pre-train the LSTM model to predict entities and their relation given the sentence by joint tagging scheme, where the parameters are ψ.

Input: Episode number L.
$\mathbf{B} = \{B^1, B^2 \ldots, B^N\}$. A LSTM network model parameterized ψ.
Initialize the target network as: $\theta' = \theta = \psi$
For episode l=1 to L **do**
Shuffle B to obtain the bag sequence
$\mathbf{B} = \{B^1, B^2, \ldots, B^N\}$
Foreach $B^K \in \mathbf{B}$ **do**
Sample the entities and relations for each sentence in B^K with θ'
Compute reward $R(s_i|B)$ for current sentence
$R(s_i|B) = \sum_{j=i}^{n} \gamma^{n-j} r_j$
end
Update θ in the model:

$$\nabla J_\theta = \sum_{i=1}^{n} \nabla p(a_i|s_i,\theta') R(s_i|B)$$

End

4 EXPERIMENT

4.1 Data

This paper adopted ACE2005 which previous studies has reported on to evaluate the model and use three common metrics: precision(P), recall(R) and F1-score(F1). ACE2005 includes three parts: English, Chinese and Arabic. In order to compare with most previous work, this paper use the same way (Li 2014, Ji 2014) with the English dataset to split and preprocess the data. There are 351 training documents, 80 validation documents and 80 testing documents. ACE2005 includes three parts: English, Chinese and Arabic and defines 7 coarse-grained relation types. Relation types are “PHYS”(Physical), “GEN-AFF”(Gen-Affiliation), “ART”(Artifact), “PART-WHOLE”(Part-Whole), “PER-SOC”(Person-Social), “ONG-AFF”(Org-Affiliation) and “METONYMY”(Metonymy). In the process of extraction, entities and relations can be extracted in a sentence simultaneously.

4.2 Hyperparameters

This paper employed word2vec to train the word embeddings and set the dimension of word embeddings as 300, the number of LSTM units is fixed at 300 and dropout rate is 0.5. The batch size is fixed to 160 and episode number is 20. This paper uses Adam to optimize parameters during the training procedure. The learning rate is 0.002 and set $\gamma = 1$ because in this task, the order of sentences in bag should not influence the predicted result (Zeng 2018, He 2018, Liu 2018).

Table 2: Entity and relationship extraction results.

Method	Entity			Relation		
Score	P(%)	R(%)	F1(%)	P(%)	R(%)	F1(%)
Pipeline (Li 2014, Ji 2014)	83.2	73.6	78.1	67.5	39.4	49.8
Joint w/Global (Li 2014, Ji 2014)	85.2	76.9	80.8	68.9	41.9	52.1
SPTree (Miwa 2016, Bansal 2016)	82.9	**83.9**	83.4	57.2	**54.0**	**55.6**
RL	**86.7**	82.1	**84.3**	**69.7**	43.4	53.5

4.3 Baselines

The baseline used in this paper is the latest method of the ACE2005 dataset, including a classic pipeline model (Li 2014, Ji 2014), a joint feature-based model called joint w/Global (Li 2014, Ji 2014) and an end-to-end neural network-based model called SPTree (Miwa 2016, Bansal 2016). The classic pipeline method (CRF+ME) trains a linear chain conditional random field for entity extraction and maximum entropy model for relational extraction. SPTree proposes a new end-to-end relation extraction model that represents word sequences and dependent tree structures through LSTM-RNNs of bidirectional sequences and bidirectional tree structures. Joint w/Global developed a number of effective global features to capture the interdependency among entity mentions and relations.

4.4 Results

The results of the separate extraction of entities and relation are shown in Table 2. The combined results of the joint extraction are shown in Table 3, Where RL is the method of this paper. The F1 value reached 52.3%, which is the best result compared to the existing method. It illustrates the effectiveness of the proposed model in the task of joint extraction of entities and their relationships.

Table 3: Joint extraction prediction results.

Model	P(%)	R(%)	F1(%)
Pipeline (Li 2014, Ji 2014)	65.1	38.1	48.1
Joint w/Global (Li 2014, Ji 2014)	65.4	39.8	49.5
SPTree (Miwa 2016, Bansal 2016)	**65.8**	42.9	51.9
RL	65.6	**43.5**	**52.3**

As can be seen from the data in the table 2, SPTree achieves the highest recall rate for entities and relations and also is best at the F1 value of the relations, they are respectively 83.0%, 54.0 and 55.6%. However, the model RL in this paper has the highest precision in terms of entities and relations and also is best at the F1 value of the entities, they are respectively 86.7%, 69.7% and 84.3%. In the joint extraction of entities and relations from the table 3, the highest F1 value was also achieved. In order to facilitate a clear understanding of the indicators obtained by various models, the histogram 3 characterizes the metrics.

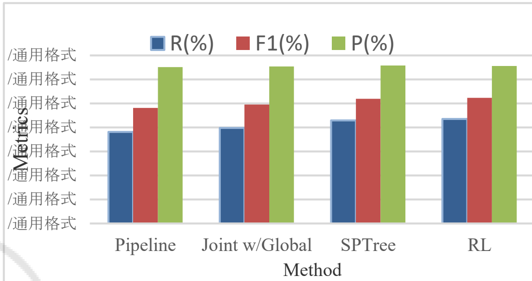

Figure 3: Comparison of histograms of metrics obtained by each model.

Table 4: Relation of "PlaceofBirth" predicted by the models.

Sentences whose relation type is "PlaceofBirth"	RL	PCNN+ Max	PCNN+ ATT
For the two most powerful Americans in **Iraq**, Gen. George W. Casey Jr. and Ambassador Zalmay Khalilzad, as for the Iraqi dignitaries who had gathered here, it was a symbolic moment: a ceremony on a bluff high above the Tigris River at which the Americans formally returned the largest of **Saddam Hussein**'s palace complexes to Iraqi sovereign control, 31 months after invading troops had seized it for use as an American base.	PlaceofBirth	NA	PlaceofB irth
It seems inevitable that he's coming back, center fielder **Randy Winn** said Wednesday in **Los Angeles** as the Giants completed a three-game series with the Dodgers.	PlaceofBirth	PlaceofBirth	PlaceofB irth
The group moved its headquarters to France and then to **Iraq** in 1986, when it set up a well-financed military base under the protection of **Saddam Hussein**.	PlaceofBirth	NA	PlaceofB irth
Ingrid Rossellini said she was outraged by the conceit, and by the showing of a widely known scene from the director's **Rome**: Open City in which a German soldier shoots a character, played by **Anna Magnani**, in the stomach.	PlaceofBirth	PlaceofBirth	NA
American commanders have described the violence in **Iraq** as being caused variously by a mix of foreign terrorists, Sunni loyalists to **Saddam Hussein**, Shiite radicals and criminals.	PlaceofBirth	NA	PlaceofB irth

5 DISCUSSION

Entity and relation extractions are always handled in an unbalanced corpus, where there is no relation between entities in most statements. Therefore, the public corpus-New York Time data set is used for verification. The New York Times corpus is a distant supervision dataset created by aligning the freebase knowledge base with the New York Times corpus. In order to evaluate how accurately the decision of the Policy Gradient reinforcement learning algorithm module is carried out, taking the current classical mainstream comparison research methods PCNN+CrossMax (Jiang 2016, Wang 2016, Li 2016) and PCNN+ATT (Lin 2016, Shen 2016, Liu 2016) to experiment for relation extraction. The precision/recall curves of those models in Figure 4. It can be seen from the model presented in this paper outperforms other two methods. The maximum value of F1-Score of this paper's model can reach out 42.19%, although PCNN+CrossMax got the highest precision.

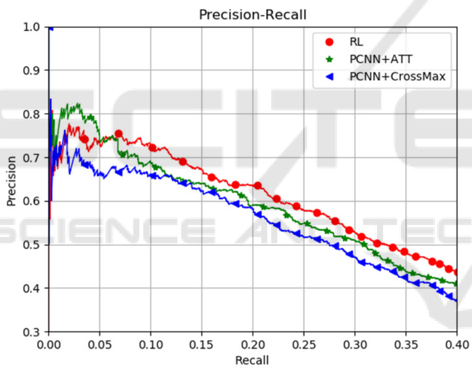

Figure 4: Comparison between the PCNN+CrossMax and PCNN+ATT.

By using the distant supervision as the guide of reinforcement learning so that we can understand that the model in this paper can better predict the relation among the sentence. A real case is shown in table 4. As can be seen from the table, the results predicted by the model in this paper are correct, while the other two models have certain errors

6 CONCLUSIONS

In view of the shortcomings of the pipeline method, this paper proposes a new model using the reinforcement learning algorithm, which can realize the joint extraction of entities and relations at the bag level by using the combination of the joint labeling strategy and the special reward function. This model mainly consists of two modules: one is joint extractor based on the LSTM network with annotation extraction strategy, and the other is the Policy Gradient reinforcement learning algorithm for training. Experiments show that the proposed model can complete the joint extraction of entities and relations at the bag level and achieve better results.

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