Explore BiLSTM-CRF-Based Models for Open Relation Extraction

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Abstract

Extracting multiple relations from text sentences is still a challenge for current Open Relation Extraction (Open RE) tasks. In this paper, we develop several Open RE models based on the bidirectional LSTM-CRF (BiLSTM-CRF) neural network and different contextualized word embedding methods. We also propose a new tagging scheme to solve overlapping problems and enhance models’ performance. From the evaluation results and comparisons between models, we select the best combination of tagging scheme, word embedder, and BiLSTM-CRF network to achieve an Open RE model with a remarkable extracting ability on multiple-relation sentences.

1 Introduction

Open Relation Extraction (Open RE) is an important task of Natural Language Processing (NLP), which involves extracting structured relation representations from text sentences. In an Open RE system, relations are expressed by predicates and their arguments. For instance, Figure 1 shows that in the example sentence “Joe Biden visited Apple Inc. founded by Steve Jobs”, “visited” is the predicate and “Joe Biden” and “Apple Inc.” are the arguments of the relation while “founded by” indicates another relation between “Apple Inc.” and “Steve Jobs”. Nowadays, Open RE has been applied widely in knowledge-based applications such as question-answering intelligence, dialogue systems, ontology building, and text comprehension (Cui et al., 2018; Jia and Xiang, 2019).

Most of the existing Open RE models such as TextRunner (Etzioni et al., 2008), Reverb (Fader et al., 2011) and OLLIE (Schmitz et al., 2012) use pattern-based matching method. But the hand-crafted patterns highly rely on rule-based or semi-supervised algorithms (Jia and Xiang, 2019). Even though using such hand-crafted patterns can extract relations accurately, it requires much more time and human resources, thereby reducing the efficiency of an Open RE task.

Recurrent Neural Network (RNN) is a popular artificial neural network that exhibits many advantages on sequence-relevant tasks. Many RNN-based models are proposed and the Long Short-term Memory (LSTM) (Hochreiter and Schmidhuber, 1997) is widely considered as one of the most reliable and effective RNN networks for building Open RE models.

To better understand the context of sentences, bidirectional LSTM (BiLSTM) has been proposed (Huang et al., 2015). It handles the input in two directions: one is from the start to the end and another is from the end to the start. This architecture shows excellent performance for prediction. Recently, the BiLSTM-CRF network has been widely applied on sequence tagging tasks such as Named Entity Recognition (NER) and Part-Of-Speech (POS) tagging (Jia and Xiang, 2019). Several state-of-the-art models are used for dynamic word representations such as CoVe (McCann et al., 2017), ELMo (Peters et al., 2018) and BERT (Devlin et al., 2018).

In this study, we build our Open RE models by applying a BiLSTM network as the encoding layer and a Conditional Random Field (CRF) layer for tagging words. We use both pre-trained word embeddings and contextualized word embedders BERT and ELMo to produce word representations and feed them into the BiLSTM-CRF neural network. We also train our BiLSTM-CRF-based mod-
els under different tagging schemes to find an Open RE model with superior performance.

2 Related Work

Generally, there are two main directions for building a supervised Open RE model in the literature. One is to create a sequence tagging model and the other is to design a sequence-to-sequence model.

Sequence Tagging Models. Stanovsky et al. (2018) introduced the first supervised Open RE model for extracting both predicates and related arguments. They used a BiLSTM network with a Softmax layer to build an RNN model which tags each word in the sentences and extract tuples that contain relations. Further, they also created a large-scale, high-quality labelled corpus to support supervised training.

Jia and Xiang (2019) presented a Hybrid Neural Tagging Model for Open RE task (HNN4ORT). They used a triple embedding layer, the Dual Aware Mechanism and Ordered Neurons LSTM (ON-LSTM) to build the hybrid neural framework (Jia and Xiang, 2019). Moreover, they also proposed the idea about changing the rule of labelling in the dataset to improve model performance.

Sequence-to-sequence Models. Open RE can also be regarded as a sequence-to-sequence (seq2seq) task based on a machine translation mechanism. Cui et al. (2018) introduced an encoder-decoder framework with multiple-LSTM layers which can generate sequences with placeholders and extract relation tuples from the output. Consider the example sentence in Figure 1, the output sequence will be “(arg0)Joe Biden(arg0)⟨rel⟩visited⟨/rel⟩(arg1)Apple Inc.(/arg1)⟨rel⟩founded by(/rel)(arg2)Steve Jobs(/arg2)”.

3 Method

3.1 Tagging Scheme

We define Open RE as a sequence tagging task. Let \( S = (w_1, w_2, ..., w_n) \) be a word sequence (i.e., a sentence) where each \( w_i \) is a word, and \( T = (t_1, t_2, ..., t_n) \) be a tagging sequence where each \( t_i \) is a tag. For tags in \( T \), we use P-B and P-I as relation tags to denote predicates, A-B and A-I as argument tags to denote arguments, and O to denote other words. For the training corpus, we use a public large-scale labeled dataset - All Words Open IE \(^1\) (AW-OIE) (Stanovsky et al., 2018). They proposed a tagging scheme in where a word sentence may generate several tagging sequences where each sequence has only one relation tag. Each tagging sequence is independent of each other so that they extended the training set to 12952 samples for supervised training.

However, this tagging scheme has overlapping problems in multiple-relation sentences. For example, in Figure 2, relation “visited” is denoted as P-B in a tagging sequence \( T_1 \) but as O in another tagging sequence \( T_2 \). The overlapping problems cause incomplete and incorrect predictions in the sequence tagging process and impact the model performance. To solve overlapping problems, we propose a new tagging scheme that can automatically produce tagging sequences with multiple relation annotations. In Figure 2, the tagging sequence \( T_3 \) is generated by our new tagging scheme and it has multiple relation tags P0-B, P1-B and P1-I based on the order of relations. And we don’t need to

\(^1\)https://github.com/gabrielStanovsky/aw-oie
expand our training data based on the new tagging scheme.

3.2 Model Architecture

Our model consists of three layers: an embedding layer (embedder), a bidirectional LSTM (BiLSTM) layer, and a Conditional Random Field (CRF) layer.

For the embedding layer, we use pre-trained word embeddings like GloVe (Pennington et al., 2014). We also use two deep contextualized word embedders, BERT and ELMo, to produce the representation of each tag based on its context in a sentence.

Then, the word embedding sequence $X = (x_1, x_2, ..., x_n)$ is fed into a BiLSTM layer which is made up by forward and backward LSTM cells. The forward LSTM cells generate the forward hidden states $H_f = (h_{f1}, h_{f2}, ..., h_{fn})$ as follows (Cui et al., 2018).

$$h_{f(t)} = \text{LSTM}(x_t, h_{f(t-1)})$$ (1)

Similarly, the backward LSTM cells generate the backward hidden states $H_b = (h_{b1}, h_{b2}, ..., h_{bn})$.

$$h_{b(t)} = \text{LSTM}(x_t, h_{b(t-1)})$$ (2)

Then the BiLSTM layer combines forward and backward hidden states to produce the complete hidden state sequence $H = (h_1, h_2, ..., h_n)$. It also maps hidden state vectors to $k$-dimension vectors where $k$ represents the number of tags in the tagging scheme (Dai et al., 2019). Hence, the BiLSTM layer extracts and combines both the “past” and “future” features from a sentence.

The CRF layer takes the output of the BiLSTM layer and starts the sequence tagging process. It has the ability to make use of contextualized tag information to produce a better tagging accuracy (Huang et al., 2015). As a result, we recognize relation tags \textbf{P-B} (New Tagging Scheme: \textbf{P0-B}, \textbf{P1-B}...) from the output tagging sequence to finish the Open RE task.

4 Experiments

4.1 Data

For the training data, we use the AW-OIE data corpus which is derived from OIE2016 by QA-SRL annotations (He et al., 2015). We extract a training set with 3300 multiple-relation sentences with 12952 corresponding tagging sequences. Each sentence has about 4 relations. The tags are extended from BIO tagging scheme with a head notation \textbf{A} to denote arguments (\textbf{A0-B}, \textbf{A0-I}) and \textbf{P} to denote relations (\textbf{P-B}, \textbf{P-I}) (Stanovsky et al., 2018).

For the testing data, we collect testing sets from previous Open RE works to evaluate the performance of our Open RE model. Table 1 depicts the three testing sets in the experiments: AW-OIE, Wikipedia and NYT (Del Corro and Gemulla, 2013). We extract another 634 sentences with 1724 relations from the AW-OIE corpus to build the AW-OIE testing set. Additionally, the Wikipedia testing set contains 376 sentences with 985 relations, and the NYT testing set has 258 sentences with 739 relations. The average number of relations within each sentence is close to 3, and these testing sets can be used for evaluating the performance of our Open RE model on multiple-relation extractions.

| Dataset   | Sentence | Relation | Avg (R/S) |
|-----------|----------|----------|-----------|
| AW-OIE    | 634      | 1724     | 2.7       |
| Wikipedia | 376      | 985      | 2.6       |
| NYT       | 258      | 739      | 2.9       |

Table 1: Profile of testing sets in the experiments. Avg (R/S) means average number of relations per sentence.

4.2 Word Embeddings

In the experiments, we combine the BiLSTM-CRF network with different word embedding methods.

\textbf{GloVe-BiLSTM-CRF}. We build the GloVe-BiLSTM-CRF model by applying the pre-trained word embeddings GloVe (Pennington et al., 2014). We choose 200-dimension vectors for capturing the word-level semantics.

\textbf{W2V-BiLSTM-CRF}. We also select another 300-dimension Word2Vec (Mikolov et al., 2013) pre-trained vectors from the Google News dataset to build the W2V-BiLSTM-CRF model.

\textbf{BERT-BiLSTM-CRF}. We use a pre-trained BERT model from Google Research (Turc et al., 2019) to generate deep contextualized word representations. We choose the BERT-Base, Multilingual Cased version.

\textbf{ELMo-BiLSTM-CRF}. We build the ELMo-BiLSTM-CRF model by using an original pre-trained ELMo model provided by AllenNLP (Peters et al., 2018) as the word embedder.

4.3 Parameter Settings

The experimental environment is on the Amazon Web Service (AWS) platform with the setting of 16
vCPU, 2.9 GHz Intel Xeon E5-2666 v3 Processor, RAM. We implement models on PyTorch (Paszke et al., 2019) and use RayTune (Liaw et al., 2018) for hyper-parameters tuning.

For both the GloVe-BiLSTM-CRF model and the W2V-BiLSTM-CRF model, we initialize the learning rate as 0.01 with a weight decay of 0.0001. The mini-batch size is set to 50 and we train the models in 100 epochs.

For the BERT-BiLSTM-CRF model and the ELMo-BiLSTM-CRF model, we set most hyper-parameters based on prior work (Devlin et al., 2018; Peters et al., 2018) and only changes token representations of tags. We also train these two models in 100 epochs.

We use Adam (Kingma and Ba, 2014) optimizer for all models in the experiment. Meanwhile, we train the models under Stanovsky et al. (2018) tagging scheme and the new tagging scheme with the same testing sets to make a fair comparisons.

### Evaluation

The evaluation metrics in our experiment are precision, recall and F1-score. The recall values are used to evaluate the rate of how many relations are correctly predicted. Furthermore, we define a new measurement called **Predicate Matching Score** (PMS) to represent the correct relation extraction rate for evaluating the model performance. The PMS is able to indicate the performance of a model based on different tagging schemes. \( \text{PMS}(\%) = \frac{\sum_{i=1}^{l} |\text{Predict}(R_i)|}{\sum_{i=1}^{l} |\text{True}(R_i)|} \times 100\% \)

Table 2 shows an example of computing PMS. We first remove incorrect predicted relations, stopwords and modal verbs like "could" to guarantee that the predicted relation list is a sublist of true relation list. Then we compare the extracted relations with the true relations and calculate the PMS of the testing set. As sequence tagging tasks always produce non-relation tags, using PMS to assess the Open RE model can mitigate the influence of arguments prediction and focus on the models’ performance of relation prediction.

### Results and Discussion

#### 5.1 Results

Table 3 shows the results of the Open RE models on different testing sets respectively. It also displays the results of NTS-GloVe-BiLSTM-CRF, NTS-W2V-BiLSTM-CRF, NTS-BERT-BiLSTM-CRF and NTS-ELMo-BiLSTM-CRF which represent models that combined with the New Tagging Scheme (NTS). And we also select the results on the same testing sets from previous work proposed by Jia and Xiang (2019) as the baseline.

#### 5.2 Discussion

We investigate the experimental results and observe that GloVe-BiLSTM-CRF, W2V-BiLSTM-CRF and ELMo-BiLSTM-CRF models all have high precision with relatively low recall and PMS in the tagging scheme of Stanovsky et al. (2018). The BERT-BiLSTM-CRF model performs well but
the results are not competitive enough. Table 4 provides several RE examples from the experiments. The high precision values result from a small number of false-positive (FP) predictions so that precision is unable to precisely reflect the model performance. The low recall and PMS values indicate the extraction ability is poor because of the existence of incomplete and incorrect relation extractions. We discover that too many O tags in Stanovsky et al. (2018) tagging scheme causes overlapping problems in tagging sequence, leading to the poor recall and PMS values of these models.

Table 3 also shows the evaluation results of these models based on the new tagging scheme. We find both recall and PMS values have increased considerably in these models. NTS-GloVe-BiLSTM-CRF model and NTS-BERT-BiLSTM-CRF model have remarkable performance i.e., nearly 94% relations are correctly extracted from the testing sets. BERT-BiLSTM-CRF has better results than GloVe-BiLSTM-CRF in the tagging scheme of Stanovsky et al. (2018). Nevertheless, from the second example in Table 4, NTS-BERT-BiLSTM-CRF can the extract relation phrase "sought by" completely but NTS-GloVe-BiLSTM-CRF can only identify the word "sought". We believe the size of testing sets is one limitation that makes the results from NTS-GloVe-BiLSTM-CRF and NTS-BERT-BiLSTM-CRF very close.

We also notice the increase in recall and PMS from NTS-W2V-BiLSTM-CRF and NTS-ELMo-BiLSTM-CRF. Both models perform better than previous works like Reverb, OLLIE and OpenIE4. However, their performances are not competitive when compared with other advanced Open RE models such as HNN4ORT (Jia and Xiang, 2019). Meanwhile, for NTS-W2V-BiLSTM-CRF, there is a decrease of precision from approximately 0.88 to 0.55 which reflects the existence of a large number of FP predictions under the new tagging scheme.

According to the evaluation results, we find that the NTS-BERT-BiLSTM-CRF outperforms other BiLSTM-CRF based models. Our new tagging scheme can enhance the Open RE models’ performance. The NTS-BERT-BiLSTM-CRF displays excellent performance on the Open RE task and
Table 4: Examples of experimental output of our embedder-BiLSTM-CRF models using two tagging schemes. Bold blue tags are relation tags of the new tagging scheme. Green tags reflect mispredicted tags.

| Sent. 1 | While **pursuing** his MFA at Columbia University, Scieszka **painted** apartments |
|---------|----------------------------------------------------------------------------------|
| GloVe   | While [pursuing] _P−B_ his MFA at Columbia University, Scieszka [painted] _P−B_ apartments |
| W2V     | While [pursuing] _O_ his MFA at Columbia University, Scieszka [painted] _P−B_ apartments |
| BERT    | While [pursuing] _P−B_ his MFA at Columbia University, Scieszka [painted] _P−B_ apartments |
| ELMo    | While [pursuing] _O_ his MFA at Columbia University, Scieszka [painted] _P−B_ apartments |

| Sent. 2 | Mrs. Marcos has not **admitted** that she **filed** any documents such as those **sought by** the government |
|---------|------------------------------------------------------------------------------------------------|
| GloVe   | Mrs. Marcos has not [admitted] _P−B_ that she [filed] _O_ any documents such as those [sought] _P−B_ [by] _O_ the government |
| W2V     | Mrs. Marcos has not [admitted] _P−B_ that she [filed] _O_ any documents such as those [sought] _P−B_ [by] _O_ the government |
| BERT    | Mrs. Marcos has not [admitted] _P−B_ that she [filed] _P−B_ any documents such as those [sought] _P−B_ [by] _O_ the government |
| ELMo    | Mrs. Marcos has not [admitted] _P−B_ that she [filed] _O_ any documents such as those [sought] _P−B_ [by] _O_ the government |

especially achieves over 94% correctly extractions in multiple-relation sentences.

6 Conclusion

In this paper, we propose and explore several BiLSTM-CRF based models for open relation extraction. We also introduce a new tagging scheme to solve overlapping problems and improve the performance of models. Experimental results indicate that NTS-BERT-BiLSTM-CRF and NTS-GloVe-BiLSTM-CRF perform well in correctly and completely extracting multiple relations from sentences.

In future work, we are going to explore joint extraction methods (Zheng et al., 2017; Ni et al., 2021, 2023b,d,c,a; Chen et al., 2022; Ni, 2024; Song et al., 2023) to extract both relations and entities. Furthermore, we will expand datasets and models to work on some cross-lingual extraction (Zhang et al., 2017) tasks such as extracting relations from other languages such as French, Latin and Mandarin.

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