TPLinker: Single-stage Joint Extraction of Entities and Relations Through Token Pair Linking

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Abstract

Extracting entities and relations from unstructured text has attracted increasing attention in recent years but remains challenging, due to the intrinsic difficulty in identifying overlapping relations with shared entities. Prior works show that joint learning can result in a noticeable performance gain. However, they usually involve sequential interrelated steps and suffer from the problem of exposure bias. At training time, they predict with the ground truth conditions while at inference it has to make extraction from scratch. This discrepancy leads to error accumulation. To mitigate the issue, we propose in this paper a one-stage joint extraction model, namely, TPLinker, which is capable of discovering overlapping relations sharing one or both entities while immune from the exposure bias. TPLinker formulates joint extraction as a token pair linking problem and introduces a novel handshaking tagging scheme that aligns the boundary tokens of entity pairs under each relation type. Experiment results show that TPLinker performs significantly better on overlapping and multiple relation extraction, and achieves state-of-the-art performance on two public datasets[1].

1 Introduction

Extracting entities and relations from unstructured texts is an essential step in automatic knowledge base construction (Takanobu et al., 2019). Traditional pipelined approaches first extract entity mentions and then classify the relation types between candidate entity pairs. However, due to the complete separation of entity detection and relation classification, these models ignore the interaction and correlation between the two subtasks, being susceptible to cascading errors (Li and Ji, 2014).

In the last few years, there has been increasing research interest in building joint models to simultaneously extract entities and relations. Recent works show that joint learning approaches can effectively integrate the information of entity and relation, and therefore achieve better performance in both subtasks (Dai et al., 2019; Tan et al., 2019). Zheng et al. (2017) proposed a unified tagging scheme to convert joint extraction to a sequence labeling problem but lacks the elegance to identify overlapping relations: one entity may participate in multiple relations in the same text (Figure 1).

Most existing models in handling EntityPairOverlap (EPO) and SingleEntiyOverlap (SEO) cases can be categorized into two classes: decoder-based and decomposition-based. Decoder-based models use encoder-decoder architecture where the decoder extracts one word or one tuple at a time like machine translation models (Zeng et al., 2018; Nayak and Ng, 2020). Decomposition-based models first distinguish all the candidate subject entities that may be involved with target relations, then label corresponding object entities and relations for each extracted subject (Li et al., 2019; Yu et al., 2020; Wei et al., 2020). Although these methods have achieved reasonable performance, they all suffer from the same problem:

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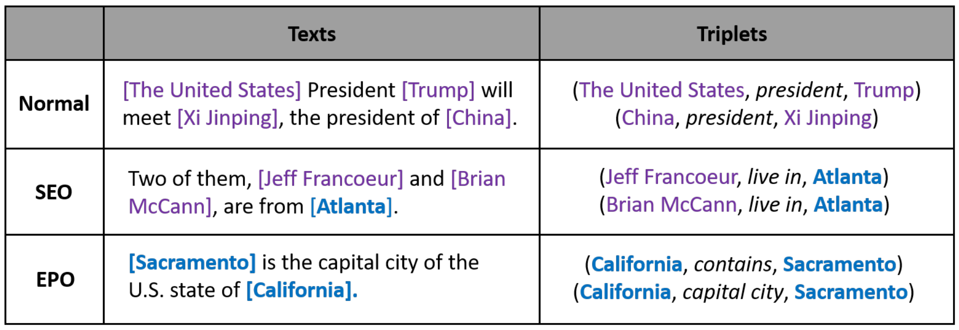
[1]The source code of this paper can be obtained from https://github.com/131250208/JointExtraction



	Texts	Triplets
Normal	[The United States] President [Trump] will meet [Xi Jinping], the president of [China].	(The United States, *president*, Trump) (China, *president*, Xi Jinping)
SEO	Two of them, [Jeff Francoeur] and [Brian McCann], are from **[Atlanta]**.	(Jeff Francoeur, *live in*, **Atlanta**) (Brian McCann, *live in*, **Atlanta**)
EPO	**[Sacramento]** is the capital city of the U.S. state of **[California].**	(**California**, *contains*, **Sacramento**) (**California**, *capital city*, **Sacramento**)

o

Figure 1: Examples of the Normal, SingleEntityOverlap (SEO), and EntityPairOverlap (EPO) cases. The overlapping entities are marked in blue.

exposure bias. For the decoder-based method, at training time, the ground truth tokens are used as context while at inference the entire sequence is generated by the resulting model on its own, and hence the previous tokens generated by the model are fed as context. As a result, the predicted tokens at training and inference are drawn from different distributions, namely, from the data distribution as opposed to the model distribution(Zhang et al., 2019). Similarly, the decomposition-based method uses the gold subject entity as specific input to guide the model extract object entities and relations during the training process while at inference the input head-entity is given by a trained model, leading to a gap between training and inference.

In this paper, we present a one-stage method for joint extraction of entities and overlapping relations, namely TPLinker, which bridges the gap between training and inference. TPLinker transforms the joint extraction task as a **T**oken **P**air **Link**ing problem. Given a sentence, two positions p_1, p_2 and a specific relation r, TPLinker is to answer three Yes/No pseudo questions: "Whether p_1 and p_2 are the start and end positions of the same entity respectively?", "Whether p_1 and p_2 are the start positions of two entities with r relation respectively?" and "Whether p_1 and p_2 are the end positions of two entities with r relation respectively?" To this end, we design a handshaking tagging scheme that annotates three token link matrices for each relation to answer the above three questions. These link matrices are then used to decode different tagging results, from which we can extract all entities and their overlapping relations. Intuitively, TPLinker does not contain any inter-dependency extraction steps, so it avoids the dependence on ground truth conditions at training time, realizing the consistency of training and testing.

We evaluate our method on two public datasets: NYT (Riedel et al., 2010) and WebNLG (Gardent et al., 2017). Experimental results show that TPLinker outperforms previous works and achieves the state-of-the-art results on the benchmark datasets. Further analysis demonstrates that TPLinker significantly improves the performance on Normal, SEO, EPO, and multiple relation extraction.

2 Related Work

Researchers proposed several methods to extract both entities and relations. Traditional pipelined methods (Zelenko et al., 2003; Chan and Roth, 2011) neglect the relevance of entity extraction and relation prediction. To resolve this problem, several joint models have been proposed. Feature-based works (Yu and Lam, 2010; Miwa and Sasaki, 2014) need a complicated process of feature engineering and heavily depend on NLP tools for feature extraction. Neural models for joint relation extraction are investigated in recent studies (Gupta et al., 2016; Zheng et al., 2017), they show promising results but completely giving up overlapping relations. To address this problem, a variety of neural networks for joint extraction of entities and overlapping relations are proposed. Dai et al. (2019) extracted triplets by tagging one sentence for n times with a position-aware attention mechanism. Tan et al. (2019) solved this task via ranking with translation mechanism. Takanobu et al. (2019) firstly determined relations and then recognized entity pairs via reinforcement learning. Li et al. (2019) cast joint extraction as a multi-turn QA problem and generated questions by relation-specific templates. Sun et al. (2019) constructed an entity-relation bipartite graph to perform inference on entity types and relation types. Yu et al. (2020) presented a unified sequence labeling framework based on a novel decomposition strategy. However,

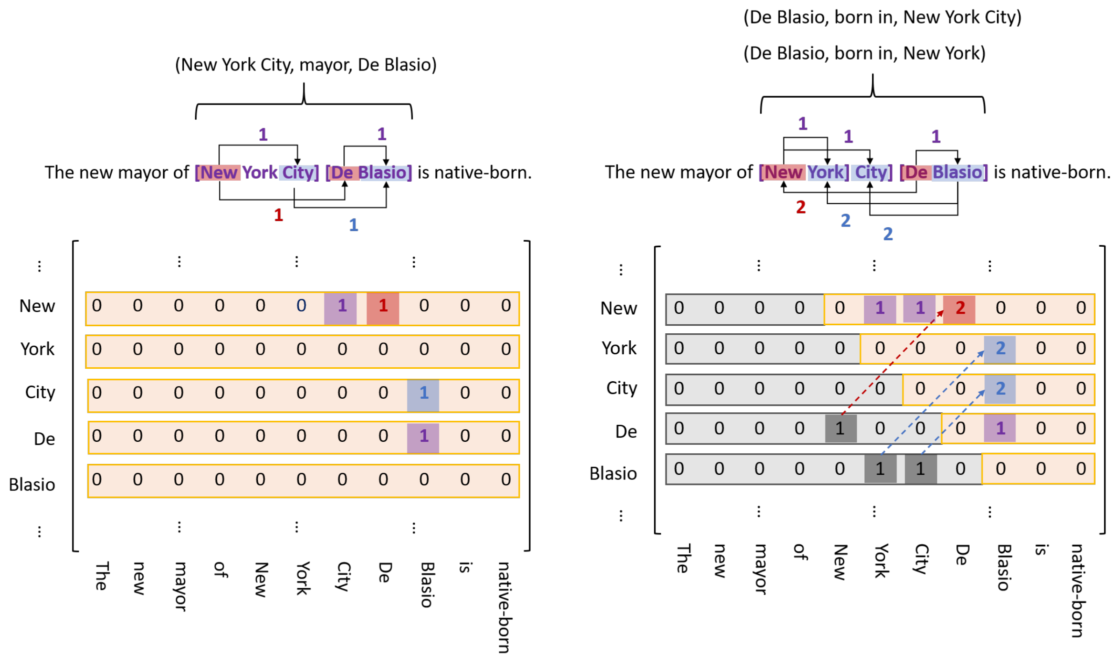

(New York City, mayor, De Blasio)
The new mayor of [New York City] [De Blasio] is native-born.
(De Blasio, born in, New York City)
(De Blasio, born in, New York)
The new mayor of [New York] City] [De Blasio] is native-born.
New
York
City
De
Blasio
The
new
mayor
of
New
York
City
De
Blasio
is
native-born

Figure 2: (Best viewed in color.) **Left**: A tagging matrix. For the convenience to illustrate, we show all tags in one matrix, in which each color corresponds to a specific kind of tag. **Right**: An example of the Handshaking Tagging Scheme, the region in shade is not included in the tag sequence.

these methods can only recognize SEO relations in the sentence and fail to extract EPO triplets.

To handle the EPO cases, Zeng et al. (2018) proposed a sequence-to-sequence model to decode overlapping relations but fail to generate multi-word entities. As the improvement, Nayak and Ng (2020) employed an encoder-decoder model where the decoder extracts one word at a time like machine translation models. Besides, Wei et al. (2020) proposed a novel cascade binary tagging framework that first identifies all possible subject entities in a sentence then identifies all possible relations and object entities for each subject entity. Actually, these methods decompose the extraction of overlapping relations into several inner-dependency steps, since the decoder needs a recursive decoding process and cascade tagging has to identify subject entities in advance. Such decomposition makes the task easy to conduct but inevitably causes the exposure bias problem, which leads to error accumulation. At training time, they predict the triplets with the ground truth tokens or subjects while at inference they have to rely on the predicted results. In this paper, we propose a unified tagging method to extract entities and overlapping relations. Different from previous methods, our model performs in one stage and generates triplets without a gap between training and inference.

3 Methodology

In this section, we first introduce our handshaking tagging scheme and its decoding algorithm. Then we detail the TPLinker model structure.

3.1 Handshaking Tagging Scheme

3.1.1 Tagging

According to the insight that a triplet (s, r, o) can be determined by aligning the boundary tokens of subject entity s and object entity o conditioned on the relation r, we realize one-stage joint extraction by tagging token pairs with link labels.

As shown in the left panel of Figure 2, given a sentence, we enumerate all possible token pairs and use matrices to tag token links. Formally, three types of links are defined as follows[2]: **1) entity head**

[2]For ease of exposition, we use "entity/subject/object head" to represent the start position of one entity/subject/object.

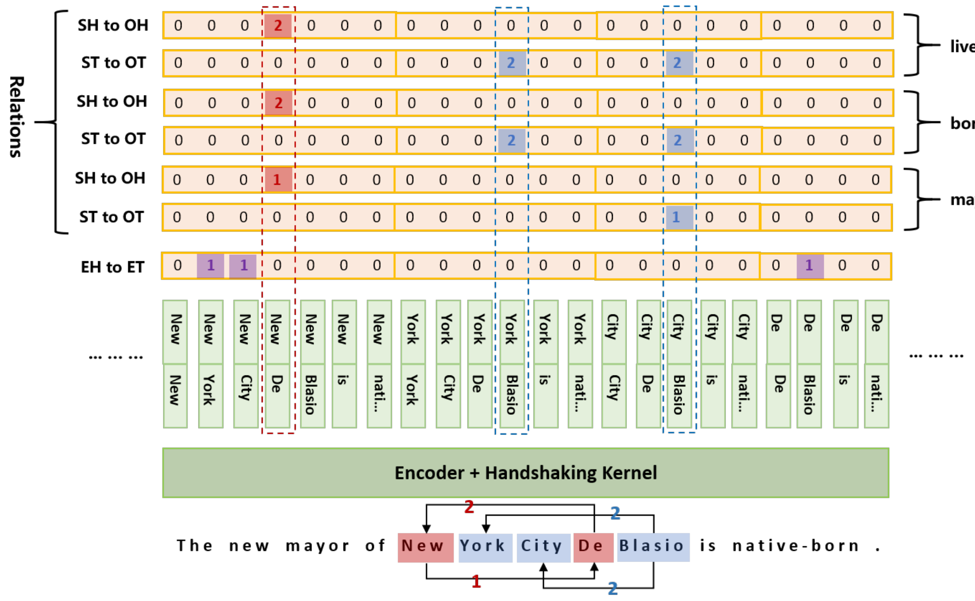

Relations
SH to OH
ST to OT
SH to OH
ST to OT
SH to OH
ST to OT
EH to ET
live in
born in
mayor
Encoder + Handshaking Kernel
The new mayor of New York City De Blasio is native-born .

Figure 3: The Framework of TPLinker. SH is short for subject head, OH is short for object head, ST is short for subject tail, and OT is short for object tail.

to entity tail (EH-to-ET). The purple tag in the matrix refers to that the two corresponding positions are respectively the start and end token of an entity. For example, "New York City" and "De Blasio" are two entities in the sentence, therefore, token pair ("New", "City") and ("De", "Blasio") are assigned with purple tag 1. **2) subject head to object head (SH-to-OH)**. The red tag means that two positions are respectively the start token of a paired subject entity and object entity. For example, there is a "mayor" relation between "New York City" and "De Blasio", so the token pair ("New", and "De") is assigned with red tag 1. **3) subject tail to object tail (ST-to-OT)**. The blue tag shares a similar logic with the red tag, which means two positions are respectively the end token of a paired subject entity and object entity. For instance, the token pair ("City", "Blasio") is assigned with blue tag 1.

As we can see from the left panel of Figure 2, the matrix is quite sparse, especially the lower triangular region. Because the entity tail is impossible to appear before the entity head, the tags in the lower triangular region are all zeros, which is a huge waste of memory. However, the object entity could appear before the corresponding subject entity, which means it is not reasonable to drop the lower triangular region directly. Before doing that, we map all tag 1 in the lower triangular region to tag 2 in the upper triangular region, then drop the lower triangular region. After doing this, it is not a complete matrix anymore, in the practical operation, we flatten the rest items into a sequence (the orange sequences in Figure 3) for the convenience of tensor calculation and use a map to remember the positions in the original matrix. The sequence is like the handshaking of all tokens, which is the reason why we refer to this scheme as the handshaking tagging scheme.

The case in the left panel of Figure 2 suggests that this tagging scheme can naturally address the SingleEntiyOverlap problem and the nested entity problem from design. In this case, "New York City" and "New York" are nested and share the same object "De Blasio", which is a challenging problem for many previous methods. However, by this tagging scheme, both the three entities and the two triplets can be easily decoded (see Section 3.1.2). However, this scheme cannot handle the EntityPairOverlap problem because different relations can not be tagged together in the same matrix for the same entity pair. To address this issue, we do the same matrix tagging job for each relation type. Note that EH-to-ET tagging is shared by all relations because it focuses on the general entity extraction without considering the specific relation types. Overall, as depicted in Figure 3, the joint extraction task is deconstructed into $2N$+1 sequence labeling subtasks where N denotes the number of pre-defined relation types, each subtask builds a tag sequence of length $\frac{n^2+n}{2}$, where n is the length of the input sentence. It seems that our

Similarly, entity/subject/object tail is defined as the end position.

tagging scheme is extremely inefficient because the length of the tagging sequence increases in a square number with increasing sentence length. Fortunately, our experiment reveals that by utilizing a light-weight tagging model on the top of the encoder, TPLinker can achieve competitive running efficiency compared with the state-of-the-art model, since the encoder is shared by all taggers (see Figure 3) and only needs to generate n token representations for once.

3.1.2 Decoding

In the case of Figure 3, ("New", "York"), ("New", "City") and ("De", "Blasio") are tagged as 1 in the EH-to-ET sequence, which means "New York", "New York City", and "De Blasio" are three entities. For relation "mayor", ("New", "De") is tagged as 1 in the SH-to-OH sequence, which means the mayor of the subject starting with "New" is the object starting with "De". ("City", "Blasio") is tagged as 1 in the ST-to-OT sequence, which means that the subject and object are the entities ending with "City" and "Blasio", respectively. Based on the information represented by these three sequences, a triplet can be decoded: ("New York City", mayor, "De Blasio").

The same logic goes for other relations, but note that the tag 2 has an opposite meaning to the tag 1, which represents a reversal link between tokens. For example, ("York", "Blasio") is tagged as 2 in the ST-to-OT sequence of relation "born in", which means "York" and "Blasio" are respectively the tail of a paired object and subject. Combined with the other two sequences, the decoded triplet should be ("De Blasio", born in, "New York").

Formally, the decoding process is summarized in Algorithm 1. For each relation, in the beginning, we extract all entity spans from the EH-to-ET sequence and map each head position to the corresponding entities starting with this position by a dictionary D. Next, for each relation, we firstly decode (subject tail position, object tail position) tuples from the ST-to-OT sequence and add them into a set E, and then decode (subject head position, object head position) tuples from the SH-to-OH sequence and lookup all possible entities starting with the head positions in the dictionary D. Finally, we iterate all candidate subject-object pairs to check whether their tail positions are in E. If so, a new triplet is extracted and added into the resulting set T.

3.2 Token Pair Representation

Given a sentence $[w_1, \cdots, w_n]$ of length n, we first map each token w_i into a low-dimensional contextual vector $\mathbf{h_i}$ by a basic encoder. Then we can generate a representation $\mathbf{h}_{i,j}$ for the token pair (w_i, w_j) as follows:

$$\mathbf{h}_{i,j} = \tanh(\mathbf{W}_h \cdot [\mathbf{h_i}; \mathbf{h_j}] + \mathbf{b}_h), j \geq i, \tag{1}$$

where $\mathbf{W}_h$ is a parameter matrix and $\mathbf{b}_h$ is a bias vector to be learned during training. Equation 1 is also denoted as Handshaking Kernel in Figure 3.

3.3 Handshaking Tagger

We utilize a unified architecture for EH-to-ET, SH-to-OH and ST-to-OT tagging. Given a token pair representation $\mathbf{h}_{i,j}$, the link label of token pair (w_i, w_j) is predicted by Equation 3.

$$P(y_{i,j}) = \mathrm{Softmax}(\mathbf{W}_o \cdot \mathbf{h}_{i,j} + \mathbf{b}_o), \tag{2}$$

$$link(w_i, w_j) = \arg\max_{l} P(y_{i,j} = l), \tag{3}$$

where $P(y_{i,j} = l)$ represents the probability of identifying the link of (w_i, w_j) as l.

3.4 Loss Function

We define the training loss as below:

$$L_{link} = -\frac{1}{N} \sum_{i=1, j \geq i}^{N} \sum_{* \in \{E,H,T\}} \log P(y^*_{i,j} = \hat{l}^*) \tag{4}$$

Here, N is the length of the input sentence, $\hat{l}$ is the true tag, E, H, and T denote the taggers of EH-to-ET, SH-to-OH and ST-to-OT, respectively.

Algorithm 1 Handshaking sequence decoding

```
Input: The EH-to-ET sequence, $S_e$;
       The SH-to-OH sequences, $\{S_h^r, r \in R\}$, where $S_h^r$ is the SH-to-OH sequence of relation $r$, $R$ is the pre-defined relation set;
       The ST-to-OT sequences, $\{S_t^r, r \in R\}$;
       The map from sequence indices to matrix indices, $M$.
Output: the predicted triplet set, $T$.
Initialize $D \leftarrow dict$        // the dictionary that maps entity head position to a set of entities that begin with this head position
Initialize $E \leftarrow set$        // the set of (subject tail position, object tail position)
Initialize $T \leftarrow set$
for $i \leftarrow 1$ to tag sequence length do
    if $S_e[i]$ = 1 then
        add $M[i]$ to $D[M[i][0]]$        // $M[i]$ is a tuple (entity head position, entity tail position)
    end if
end for
for $r \in R$ do
    for $i \leftarrow 1$ to tag sequence length do
        if $S_t^r[i]$ = 1 then
            add $M[i]$ to $E$        // $M[i]$ is a tuple (subject tail position, object tail position)
        else if $S_t^r[i]$ = 2 then
            add $(M[i][1], M[i][0])$ to $E$        // $M[i]$ is a tuple (object tail position, subject tail position)
        end if
    end for
    for $i \leftarrow 1$ to tag sequence length do
        if $S_h^r[i]$ = 1 then
            $M[i]$ is a tuple (subject head position, object head position)
            $Set_s \leftarrow D[M[i][0]]$        // Set$_s$ records the subjects beginning with $M[i][0]$
            $Set_o \leftarrow D[M[i][1]]$        // Set$_o$ records the objects beginning with $M[i][0]$
        else if $S_h^r[i]$ = 2 then
            $M[i]$ is a tuple (object head position, subject head position
            $Set_s \leftarrow D[M[i][1]]$
            $Set_o \leftarrow D[M[i][0]]$
        end if
        for $s \in Set_s$ do
            for $o \in Set_o$ do
                if $(s[1], o[1]) \in E$ then
                    add $(s, r, o)$ to $T$
                end if
            end for
        end for
    end for
end for
return $T$
```

4 Experiments

4.1 Datasets

For the convenience to compare our model with previous work, we follow the popular choice of datasets: NYT (Riedel et al., 2010) and WebNLG (Gardent et al., 2017). There are two versions of these two datasets according to the annotation standard: 1) annotating the last word of the entities and 2) annotating the whole entity span. Zeng et al. (2018), Zeng et al. (2019), Fu et al. (2019) and Wei et al. (2020) used the first version while Yu et al. (2020) chose the second version. For fair comparisons, we evaluate our model on both settings. The first version datasets are denoted as NYT* and WebNLG* and the second ones are denoted as NYT and WebNLG, respectively. Following Zeng et al. (2018), to further study the capability of TPLinker in extracting overlapping and multiple relations, we also split the test set by overlapping patterns and triplet number. The statistics are reported in Table 1.

4.2 Evaluation

In our experiments, to keep in line with previous works, we use **Partial Match** for NYT* and WebNLG*, an extracted triplet is regarded as correct if the relation and the head of both subject entity and object entity are all correct, and **Exact Match** for NYT and WebNLG, the whole spans of subject and object are needed to be matched. We follow popular choice to report the standard micro Precision (Prec.), Recall (Rec.), and F1-score as in line with all the baselines.

4.3 Implementation Details

Our TPLinker is implemented with PyTorch and the network weights are optimized with Adam (Kingma and Ba, 2014). We try two encoders in this paper. One is the combination of 300-dimensional GloVe embeddings(Pennington et al., 2014) and 2-layer stacked BiLSTM, the hidden dimension of the 2 layers

Table 1: Statistics of the datasets in our experiments. Normal set contains sentences without overlapping triple. SPO is short for Single Pair Overlapping. EPO is short for Entity Pair Overlapping. Note that the relation number of WebNLG and WebNLG* were miswritten as 246 in (Wei et al., 2020) and (Yu et al., 2020), which is the number of the original WebNLG dataset instead of the subsets they used. We recount and give the correct numbers. $\star$ marks the relation number of WebNLG*.

Model	Train	Valid	Test	Overlapping Pattern			Number of triplets					Relation
				Normal	SEO	EPO	N = 1	N = 2	N = 3	N = 4	$N \geq 5$	
NYT	56195	5000	5000	3266	1297	978	3244	1045	312	291	108	24
WebNLG	5019	500	703	246	457	26	266	171	131	90	45	216/171*

are set as 300 and 600 respectively. Dropout is applied to word embeddings and hidden states with a rate of 0.1. Another is BERT, where we use the base cased English model[3]. The learning rate is set as 1e-3/5e-5 in the backbone of BiLSTM/BERT. We also conduct Cosine Annealing Warm Restarts learning rate schedule (Loshchilov and Hutter, 2016). Following previous works (Zeng et al., 2018; Fu et al., 2019; Wei et al., 2020), we set the max length of input sentence to 100. The batch size is set as 24/6 in NYT/WebNLG. We use Tesla V100 to train the model for at most 100 epochs and choose the model with the best performance on the validation set to output results on the test set.

4.4 Comparison Models

For comparison, we employ the following models as baselines: (1) **NovelTagging**(Zheng et al., 2017) applies a novel tagging strategy that incorporates both entity and relation roles, thus the joint extraction task is converted to a sequence labeling problem. This model fails to solve the overlapping problem; (2) **CopyRE** (Zeng et al., 2018) first explores the encoder-decoder architecture for this task, trying to face overlapping problem by generating all triples in the sentence. This model can only copy the last word of an entity; (3) **MultiHead**(Bekoulis et al., 2018) first identifies all candidate entities, then formulates the task as a multi-head selection problem; (4) **GraphRel**(Fu et al., 2019) utilizes graph convolutional network to extract overlapping relations by splitting entity mention pairs into several word pairs and considering all pairs for prediction; (5) **OrderCopyRE**(Zeng et al., 2019) is an extension of CopyRE, which applies the reinforcement learning into an encoder-decoder model to generate multiple triplets; (6) **ETL-Span**(Yu et al., 2020) applies a span-based tagging strategy and hierarchically decode triplets to model the internal dependencies; (7) **WDec**(Nayak and Ng, 2020) is the improvement of CopyRE, which extracts one word at each time step, can extract overlapping relations and triplets with multi-token entities; (8) **CasRel**(Wei et al., 2020) is the state-of-the-art method on the NYT and WebNLG datasets based on the BERT backbone, which first identifies all possible head-entities in a sentence then identifies all possible relations and corresponding tail-entities for each head-entity.

4.5 Experimental Results and Analysis

4.5.1 Main Results

Table 2 reports the results of our models against other baseline methods on all datasets. We can observe that TPLinker outperforms all the baselines in terms of F1-score. Especially, TPLinker$_{BERT}$ improves 2.3 percentages on NYT*, 14.0 on NYT, and 3.6 on WebNLG over the state-of-the-art models. To validates the utility of our handshaking tagging scheme, we ablate the BERT and use BiLSTM as the substituted encoder to output results. It can be seen that TPLinker$_{BiLSTM}$ is still very competitive to existing state-of-the-art models, CasRel$_{BERT}$. What is more, TPLinker$_{BiLSTM}$ outperforms CasRel$_{BiLSTM}$ by 6.8 percentages on WebNLG*, which suggests the superiority of our scheme. Even though the two SOTA models, CasRel and ETL-Span, achieve encouraging scores, they still suffer from some problems. For CasRel, it is inherently a two-stage method, which suffers from both exposure bias and error propagation. For ETL-Span, it has the same problems with CasRel and fails to handle the EPO problem. TPLinker

[3]Available at https://huggingface.co/bert-base-cased

Table 2: Main results. Bold marks the highest score. ‡ marks results quoted directly from the original papers. † marks results reported by (Dai et al., 2019) and (Zeng et al., 2018). * marks results produced with official implementation. ⋆ marks the datasets that only annotating the last word.

Model	NYT⋆			NYT			WebNLG⋆			WebNLG		
	Prec.	Rec.	F1	Prec.	Rec.	F1	Prec.	Rec.	F1	Prec.	Rec.	F1
NovelTagging[†] (Zheng et al., 2017)	–	–	–	32.8	30.6	31.7	–	–	–	52.5	19.3	28.3
CopyRE[‡] (Zeng et al., 2018)	61.0	56.6	58.7	–	–	–	37.7	36.4	37.1	–	–	–
MultiHead[*] (Bekoulis et al., 2018)	–	–	–	60.7	58.6	59.6	–	–	–	57.5	54.1	55.7
GraphRel[‡] (Fu et al., 2019)	63.9	60.0	61.9	–	–	–	44.7	41.1	42.9	–	–	–
OrderCopyRE[‡] (Zeng et al., 2019)	77.9	67.2	72.1	–	–	–	63.3	59.9	61.6	–	–	–
ETL-Span[‡][*](Yu et al., 2020)	84.9	72.3	78.1	85.5	71.7	78.0	84.0	91.5	87.6	84.3	82.0	83.1
WDec[‡](Nayak and Ng, 2020)	**94.5**	76.2	84.4	–	–	–	–	–	–	–	–	–
CasRel$^{‡}_{LSTM}$(Wei et al., 2020)	84.2	83.0	83.6	–	–	–	86.9	80.6	83.7	–	–	–
CasRel$^{‡}_{BERT}$(Wei et al., 2020)	89.7	89.5	89.6	–	–	–	**93.4**	90.1	91.8	–	–	–
TPLinker$_{LSTM}$	83.8	83.4	83.6	86.0	82.0	84.0	90.8	90.3	90.5	**91.9**	81.6	86.4
TPLinker$_{BERT}$	91.3	**92.5**	**91.9**	**91.4**	**92.6**	**92.0**	91.8	**92.0**	**91.9**	88.9	**84.5**	**86.7**

solves all these problems and offers a bonus capability that it can extract a triplet with nested entities. For all we know, CasRel and ETL-Span cannot extract nested subject entities.

TPLinker performs well on both the dataset annotating the last word and the one annotating the whole span. Supporting this point, TPLinker achieves almost the same scores on NYT and NYT⋆, which also suggests that the dataset only annotating the last word is not always easier than the one that annotates the whole span. Even on the contrary, it could be harder because different entities may share the same last word, which makes the number of overlapping cases increase. Granted, We figure out that there is a significant gap between the performance on WebNLG and WebNLG⋆, which may disprove the above point. However, we also find out that there are 127 wrong triplets in WebNLG, containing meaningless entity "``". Plus, WebNLG has 216 relations but WebNLG⋆ has only 171, which also contributes to the performance gap. What is more, many relations in WebNLG share the same meaning, e.g. *LeaderName* and *Leader*, which confuses the model. In some cases, our model will extract both of them, but normally only one of them has been annotated in the test set. Therefore, we attribute the performance gap to these reasons. For a fair comparison with the state-of-the-art model on this dataset, we do not fix these problems in the experiments.

We can also observe that TPLinker$_{BERT}$ achieves a similar F1 score with CasRel$_{BERT}$. We consider that it is because (1) the performances on WebNLG are already saturated since extracting triplets with 171 predefined relations is very hard, especially the training data is small (5019 sentences). These methods achieving a 90+ F1 score may even surpass human-level results. (2) as described above, some similar relations are not annotated in the test data of WebNLG, which hurts the precision of TPLinker$_{BERT}$ because our model has great ability in extracting overlapping relations and achieves better recall.

4.5.2 Analysis on Different Sentence Types

To verify the ability of our model in handling the overlapping problem and extracting multiple relations, we conduct further experiments on different subsets of NYT⋆ and WebNLG⋆.

Results suggest the advantages of TPLinker in handling sentences with overlapping relations or multiple relations. As shown in Table 3, most baselines present an obvious decreasing trend with the increasing complexity of sentences. However, TPLinker presents a significant improvement on the harder sentences, ones with overlapping relations, or more than two relations. Even though CasRel also presents an increasing trend, TPLinker outperforms CasRel on all subsets except some simpler ones without overlapping or with less than three relations. Especially, TPLinker outperforms CasRel by 6.3 percentages on sentences with more than or equal to 5 relations.

[3]The original paper confuses the score on WebNLG-EPO and the score on WebNLG-SEO. The author has corrected them and updated the paper on arXiv (https://arxiv.org/abs/1909.03227). We use the correct numbers here.

Table 3: F1 score on sentences with different overlapping pattern and different triplet number. Results of baselines are all quoted directly from (Wei et al., 2020) except for ETL-Span, of which the results are reproduced by the official implementation.

Model	NYT*								WebNLG*							
	Normal	SEO	EPO	N = 1	N = 2	N = 3	N = 4	N $\geq$ 5	Normal	SEO	EPO	N = 1	N = 2	N = 3	N = 4	N $\geq$ 5
CopyRE	66.0	48.6	55	67.1	58.6	52.0	53.6	30.0	59.2	33.0	36.6	59.2	42.5	31.7	24.2	30.0
GraphRel	69.6	51.2	58.2	71.0	61.5	57.4	55.1	41.1	65.8	38.3	40.6	66.0	48.3	37.0	32.1	32.1
OrderCopyRE	71.2	69.4	72.8	71.7	72.6	72.5	77.9	45.9	65.4	60.1	67.4	63.4	62.2	64.4	57.2	55.7
ETL-Span	88.5	87.6	60.3	85.5	82.1	74.7	75.6	76.9	87.3	91.5	80.5	82.1	86.5	91.4	89.5	91.1
CasRel$_{BERT}$	87.3	91.4	92	88.2	90.3	91.9	94.2	83.7	**89.4**	92.2[5]	94.7[5]	**89.3**	**90.8**	94.2	92.4	90.9
TPLinker$_{LSTM}$	80.7	85.5	86.5	80.8	85.4	85.8	87.8	81.5	86.2	91.4	92.5	85.9	89.1	92.9	92.4	91.4
TPLinker$_{BERT}$	**90.1**	**93.4**	**94.0**	**90.0**	**92.8**	**93.1**	**96.1**	**90.0**	87.9	**92.5**	**95.3**	88.0	90.1	**94.6**	**93.3**	**91.6**

Table 4: Comparison on Computational Efficiency. Params$_{all}$ denotes the number of parameters of the entire model. Prop$_{encoder}$ is the proportion of encoder parameters in the total model parameters. Inference Time represents the the average time (ms) the model takes to process a sample. † marks the inference time when the batch size is set to 1.

Model	NYT*			WebNLG*		
	Params$_{all}$	Prop$_{encoder}$	Inference Time	Params$_{all}$	Prop$_{encoder}$	Inference Time
CasRel$_{BERT}$	107,719,680	99.96%	54.0	107,984,216	99.76%	76.8
TPLinker$_{BERT}$	109,602,962	98.82%	15.2 / 82.7†	110,281,220	98.21%	25.6 / 112.6†

4.5.3 Analysis on Computational Efficiency

Table 4 shows the comparison of computational efficiency between CasRel$_{BERT}$ and TPLinker$_{BERT}$. In this comparison experiment, we use the official implementation and default configuration of CasRel$_{BERT}$ to produce the statistics data. In the inference phase, the decoding speed of TPLinker$_{BERT}$ is almost 3.6 times as CasRel$_{BERT}$. Since the number of subjects is uncertain in a given sentence, it is difficult for CasRel$_{BERT}$ to predict objects in batch for each subject. In the official implementation, CasRel$_{BERT}$ is restricted to processes one sentence at a time, which means it is seriously inefficient and difficult to deploy. On the contrary, TPLinker$_{BERT}$ is capable of handling data in batch mode because it is a one-stage model. Besides, even though we set the batch size of TPLinker$_{BERT}$ to 1, the inference speed is still competitive, which again confirms the efficiency of TPLinker$_{BERT}$. Actually, CasRel$_{BERT}$ and TPLinker$_{BERT}$ both use BERT as the basic encoder, which is the most time-consuming part and takes up the most of model parameters, so the time cost of handshaking tagging is not significant.

5 Conclusion

In this paper, we propose an end-to-end sequence labeling model TPLinker for joint extraction of entities and relations based on a novel handshaking tagging strategy, by which the joint extraction task is converted to a token pair linking game. To the best of our knowledge, TPLinker is the first one-stage joint extraction model that can extract all kinds of overlapping relations without the influence of exposure bias. Experimental results show that our model outperforms all baselines and achieves a new state-of-the-art on two public datasets. Further analysis especially demonstrates the capabilities of our model on handling sentences with overlapping relations and multiple relations. The results also prove that it is of benefit to close up the gap between training and inference. In the future, we would like to generalize the token linking idea and explore its performance on other information extraction problems, such as nested name entity extraction and event extraction.

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