Boosting Span-based Joint Entity and Relation Extraction via Sequence Tagging Mechanism

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Abstract
Span-based joint extraction simultaneously conducts named entity recognition (NER) and relation extraction (RE) in text span form. Recent studies have shown that token labels can convey crucial task-specific information and enrich token semantics. However, as far as we know, due to completely abstain from sequence tagging mechanism, all prior span-based work fails to use token label information. To solve this problem, we propose Sequence Tagging enhanced Span-based Network (STSN), a span-based joint extraction network that is enhanced by token BIO label information derived from sequence tagging based NER. By stacking multiple attention layers in depth, we design a deep neural architecture to build STSN, and each attention layer consists of three basic attention units. The deep neural architecture first learns semantic representations for token labels and span-based joint extraction, and then constructs information interactions between them, which also realizes bidirectional information interactions between span-based NER and RE. Furthermore, we extend the BIO tagging scheme to make STSN can extract overlapping entity. Experiments on three benchmark datasets show that our model consistently outperforms previous optimal models by a large margin, creating new state-of-the-art results with a large margin.

1 Introduction
Joint entity and relation extraction aims to simultaneously detect entities and semantic relations among these entities from unstructured texts. It serves as a step stone for many downstream tasks such as question answering, knowledge base population, and has recently become a major focus of NLP researches.

Generally, joint entity and relation extraction can be classified into two categories: sequence tagging based mode (Li and Ji, 2014; Miwa and Bansal, 2016; Katiyar and Cardie, 2017; Ye et al., 2019; Lin et al., 2020; Zhao et al., 2020) and span-based mode. Recently, extensive span-based approaches have been investigated due to its good performance (Luan et al., 2018; Dixit and Al-Onaizan, 2019; Eberts and Ulges, 2019; Ji et al., 2020). Typically, span-based approaches first split text into text spans as candidate entities; then form span pairs as candidate relation tuples; finally, jointly classify spans and span pairs. For example, in Figure 1, “Jack”, “Jack taught”,… are text spans; “<“Jack”, “Jack taught”>”, “<“Harvard University”>… are span pairs; and “Jack” is classified into PER, “Harvard University” is classified into Work-for. Although these approaches have achieved promising results, they still suffer from insufficient semantics of text spans, caused by excessively relying on the encoding ability of pre-trained language models, e.g., ELMo (Peters et al., 2018), BERT (Devlin et al., 2019).

Recent span-based work further enriches semantics by introducing other NLP tasks, e.g., coreference resolution (Luan et al., 2019), event detection (Wadden et al., 2019), but these work needs additional data annotations besides annotations for NER and RE, which do not exist in many datasets. Actually, prior sequence tagging based work (Miwa and Bansal, 2016; Bekoulis et al., 2018; Ye et al., 2019; Zhao et al., 2020) has shown that token BIO labels for sequence tagging based NER can convey crucial task-specific information and greatly enrich token semantics, which turns out to deliver signifi-
significant performance improvements. For example, if the model knows that “Jack” is tagged with PER label and “Harvard University” is tagged with ORG label beforehand, it can easily infer that there may exist a Work-for relation between them. However, to the best of our knowledge, all prior span-based work fails to use token label information, due to that they completely abstain from sequence tagging mechanism. Besides, by leveraging token label information in RE, prior work (Miwa and Bansal, 2016; Bekoulis et al., 2018; Ye et al., 2019; Zhao et al., 2020) constructs an information flow from NER to RE, but fails to construct an information flow from RE to NER.

To address above issues, we propose Sequence Tagging enhanced Span-based Network (STSN), a span-based joint extraction network that can leverage token BIO label information derived from sequence tagging based NER. To build STSN, we design a deep neural architecture by stacking multiple attention layers in depth. The deep neural architecture first learns semantic representations of token BIO labels (“label semantic representations” for short) for sequence tagging based NER, and token semantic representations for span-based NER and RE, and then constructs information interactions among the learned semantic representations. Subsequently, STSN decodes these fully interactive semantic representations.

Each of the deep stacked attention layers consists of three basic attention units: (1) Entity&Relation to Label Attention (E&R-L-A), which can feed back task information of span-based NER and RE to label semantic representations, aiming to make label semantic representations can better capture task-specific information; (2) Label to Entity Attention (L-E-A), which can inject NER-specific information derived from label semantic representations into token semantic representations for span-based NER; (3) Label to Relation Attention (L-R-A), which can inject RE-specific information derived from label semantic representations into token semantic representations for span-based RE.

It is worth noting that by taking E&R-L-A as medium, STSN builds bidirectional information interactions between span-based NER and RE, which will be proven to be of great significance in §4.4. Besides, L-E-A makes STSN can utilize token label information in span-based NER, which is important but all prior joint extraction work fails to do, as far as we know. For example, a model can easily classify “Harvard University” to ORG type, if it knows the span is tagged with ORG label beforehand. Moreover, to make STSN can extract overlapping entity, we extend the BIO tagging scheme to tag overlapping entity, details will be described in §4.1. Furthermore, STSN can leverage fixed-size token label embeddings by concatenation manner.

We conduct extensive experiments on ACE05, CoNLL04 and ADE to evaluate STSN. Experimental results show that STSN overwhelmingly outperforms previous best performed models on above three benchmark datasets, creating new state-of-the-art results. To the best of our knowledge, STSN is the first span-based joint extraction network that incorporates sequence tagging mechanism, making use of advantages of both span-based and sequence tagging based joint extraction.

2 Related Works

Span-based joint extraction. Span-based joint entity and relation extraction has been widely investigated. (Luan et al., 2018) propose the first published span-based model, obtaining span representations the same as (Lee et al., 2017), and sharing them in both NER and RE. (Dixit and Al-Onaizan, 2019) realize span-based extraction by obtaining span representations through a BiLSTM over concatenation of ELMo, word and character embeddings. (Eberts and Ulges, 2019) propose SpERT, which takes BERT as backbone and dramatically reduces training complexity by adopting negative sampling. (Ji et al., 2020) further improve SpERT by enriching semantic representations with local and global features. Some approaches further promote system performance by incorporating other NLP tasks. (Luan et al., 2019) propose DyGIE, a span-based joint extraction model that incorporates coreference resolution. (Wadden et al., 2019) introduce event extraction to DyGIE and propose DyGIE++. Compared to these work, our span-based model incorporates sequence tagging mechanism, and consists of cascaded attention layers to fully leverage token label information, which does not need additional data annotations.

Token label information. Recent work has proven that token BIO labels for sequence tagging based NER can convey crucial task-specific information for NLP tasks (Wang et al., 2018; Cui and Zhang, 2019). However, this crucial information has not been fully studied in joint entity and relation extraction. Generally, prior sequence tagging
based work (Miwa and Bansal, 2016; Bekoulis et al., 2018; Ye et al., 2019) explicitly concatenates fixed-size embeddings for token BIO labels to token semantic representations for RE. (Zhao et al., 2020) further propose a deep fusion manner. Limited by the sequence tagging mechanism, these work only leverages token label information in RE, and constructs a unidirectional information flow from NER to RE. In contrast, our model is in span-based mode, making it possible to use token label information in both NER and RE. Besides, our model constructs bidirectional information interactions between span-based NER and RE.

3 Model

In this section, we will describe the Sequence Tagging enhanced Span-based Network (STSN) in detail, as Figure 2 shows. For a given sentence $\mathcal{S} = (t_1, t_2, t_3, \ldots, t_n)$, where $t_i$ denotes the $i$-th token in the sentence, we first generate its semantic representations using pre-trained language models (§3.1); then, we construct a deep neural architecture by stacking multiple attention layers in depth and each layer consists of three basic attention units -- Entity&Relation to Label Attention (E&R-L-A), Label to Entity Attention (L-E-A) and Label to Relation Attention (L-R-A), which are used to build information interactions between token labels derived from sequence tagging based NER and span-based joint extraction (§3.2); finally, we design three linear decoders for sequence tagging based NER, span-based NER and RE respectively (§3.3).

3.1 Embedding Layer

We use BERT (Devlin et al., 2019) as the default word embedding generator. For $\mathcal{S}$, BERT first tokenizes it with the WordPiece vocabulary (Wu et al., 2016) to get the input sequence. For each sequence element, its input representation is the element-wise addition of WordPiece embedding, positional embedding, and segment embedding. Then, a list of input embeddings $\mathbf{H} \in \mathbb{R}^{len \times dim}$ are obtained, where $len$ is the sequence length and $dim$ is the hidden size. A series of pre-trained Transformer blocks (Vaswani et al., 2017) are then used to project $\mathbf{H}$ into BERT embedding sequence.

$$\mathcal{E}_\mathcal{S} = \{X_1, X_2, X_3, \ldots, X_{len}\}$$

Where $X_1$ and $X_{len}$ are the BERT embeddings for the specific [CLS] and [SEP] tokens. BERT may tokenize a token into several sub-tokens to alleviate out of vocabulary problem. In STSN, we apply max-pooling to BERT embeddings for the tokenized sub-tokens of one token to obtain token semantic representation (“token representation” for short), aiming to align token sequence and token representation sequence. We remove the BERT embeddings for [CLS] and [SEP], and denote the representation sequence for $\mathcal{S}$ as:

$$\hat{\mathcal{E}}_\mathcal{S} = \{\hat{X}_1, \hat{X}_2, \hat{X}_3, \ldots, \hat{X}_n\}$$

Where $\hat{\mathcal{E}}_\mathcal{S} \in \mathbb{R}^{n \times d}$ and $d$ is the BERT embedding dimension.

3.2 Attention Layer

3.2.1 Deep Stacked Neural Architecture

We deep stack multiple attention layers to construct a deep neural architecture for STSN, and each of the stacked attention layers consists of three basic attention units, i.e. E&R-L-A, L-E-A and L-R-A, as shown in Figure 2.
The deep stacked neural architecture learns three semantic representations, i.e., semantic representations of token BIO labels for sequence tagging based NER (denoted as $H_L$), token representations for span-based NER (denoted as $H_E$) and token representations for span-based RE (denoted as $H_R$), of which the dimensions keep the same. Besides, we denote $H_C$ as the concatenation of $H_E$ and $H_R$, which keeps the same dimension to $H_E$ and $H_R$ via a FFN.

$$H_C = [H_E; H_R]W^C + b^C$$

Where $W^C, b^C$ are trainable FFN parameters.

For the first stacked attention layer, $E_S$ is projected into $H^0_L, H^0_E$ and $H^0_R$ respectively, which can be formulated as:

$$[\text{Layer}]^1 = \begin{cases} H^0_C = [H^0_E; H^0_R]W^0_C + b^0_C \\ H^1_L = E_KR-L-A(H^0_L, H^0_C, H^0_E) \\ H^1_E = L-E-A(H^0_E, H^0_C, H^0_E) \\ H^1_R = L-R-A(H^0_R, H^0_C, H^0_L) \end{cases}$$

Where $W^0_C \in \mathbb{R}^{2d^2}$ and $b^0_C \in \mathbb{R}^d$ are trainable FFN parameters. We then pass the layer outputs, i.e., $H^1_L, H^1_E, H^1_R$, to the next layer and repeat this procedure in a recursive manner, until we obtain the outputs of the $N$-th layer, i.e., $H^N_L, H^N_E$ and $H^N_R$, which are taken as the final semantic representations. Now, $H^N_E$ and $H^N_R$ fully contain task-specific information and are suitable for span-based NER and RE.

As shown in Figure 2, in each stacked attention layer, we construct bidirectional information interactions among the three basic attention units. Specifically, E&R-L-A and L-E-A can directly interact with each other, as well E&R-L-A and L-R-A. Therefore, by taking E&R-L-A as medium, L-E-A and L-R-A can interact with each other too, which constructs bidirectional information interactions between span-based information and RE in essence. Besides, L-E-A makes STSN can utilize token label information in span-based NER.

3.2.2 Three basic Attention Units

As Figure 3 shows, the three basic attention units share a general neural architecture, but differ in model inputs. We first describe the general architecture, then introduce their implementation details.

**General architecture.** The general architecture has two sub-layers: the first is a multi-head attention, the second is a position-wise Feed Forward Network (FFN). A residual connection is adopted around each of the two sub-layers, followed by layer normalization. The general architecture is similar to Transformer encoder layer, but they differ in model inputs.

Multi-head attention has proven to be effective for capturing long-range dependencies by explicitly attending to all positions. Therefore, we apply the multi-head attention to capture task information and task-specific information. The multi-head attention owns a serious of $h$ parallel heads and requires three inputs, i.e., query, key, and value.

$$\text{head}_i = \text{softmax}(\frac{(QW^Q_i)(KW^K_i)T}{\sqrt{d/h}}(VW^V_i))$$

$$I = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^o$$

Where $\{Q, K, V\} \in \mathbb{R}^{n \times d}$ are query, key and value; $\{W^Q, W^K, W^V\} \in \mathbb{R}^{d \times e/h}, W^o \in \mathbb{R}^{d \times d}$ are trainable model parameters; and $I \in \mathbb{R}^{n \times d}$ is the output. The multi-head attention learns the pairwise relationship between the query and key, and finally outputs the captured information by weighted summation across all instances. Then the residual connection conducts element-wise addition of the captured information and query, accomplishing information injection in a shallow manner.

The position-wise FFN contains two linear transformations with a ReLU activation in between.

$$\text{FFN}(I) = \text{ReLU}(max(0, IW_1 + b_1)W_2 + b_2)$$

Where $\{W_1, W_2\} \in \mathbb{R}^{d \times d}$ and $\{b_1, b_2\} \in \mathbb{R}^d$ are trainable FFN parameters. By conducting linear transformation on the outputs of multi-head attention, FFN projects the captured information to the representation space of $I$, which further accomplishes information injection in a deep manner.
**E&R-L-A.** E&R-L-A (see Figure 3) takes $H_L$ as query, $H_C$ as key and value respectively, and can feed back task information of span-based NER and RE, which is captured from $H_C$, to $H_L$, aiming to make $H_L$ can better learn task-specific information.

**L-E-A and L-R-A.** L-E-A (see Figure 3) takes $H_E$ as query, $H_L$ as key and value respectively, and is capable of injecting task-specific information of span-based NER, which is captured from $H_L$, into $H_E$. Similarly, L-R-A (see Figure 3) takes $H_R$ as query, $H_L$ as key and value respectively, and can inject RE-specific information into $H_R$.

### 3.3 Decoding Layer

We propose three linear decoders for sequence tagging based NER, span-based NER and RE respectively.

**Decoder for sequence tagging based NER.** This decoder first utilizes a FFN to reduce label semantic representation, i.e., $H_L^N$, to space of token BIO label size; then utilizes $\text{softmax}$ to calculate probability distributions on the label size space.

$$\hat{y}^L = \text{softmax}(H_L^N W^L + b^L)$$

Where $W^L \in \mathbb{R}^{d_l \times d_l}$ and $b^L \in \mathbb{R}^l$ are trainable FFN parameters; $l$ is the token BIO label size. The training objective is to minimize the cross-entropy loss.

$$\mathcal{L}_L = -\frac{1}{M} \sum_{i=1}^{M} y_i^L \log \hat{y}_i^L$$

Where $y^L$ is the one-hot vector of gold token BIO label for sequence tagging based NER; $M$ is the number of token instances. For each token BIO label, we maintain a label embedding with fixed size (denoted as $H_L^N$) for it, which is trained during model training. We use gold token BIO labels during model training and predicted labels during inference.

**Decoder for span-based NER.** We first add NoneEntity type to the pre-defined entity types. Spans will be decoded into NoneEntity space if they are not predicted as entities. We formulate an arbitrary span from $S$ to help introduce the rest: $s = \{t_1, t_{i+1}, t_{i+2}, ..., t_{i+j}\}$.

We obtain span representation by concatenating token representations of span head and tail, and a span width embedding, following (Luan et al., 2018).

$$E_s = [H_{E_1}^N; H_{E_{i+j}}^N; W_{j+1}]$$

Where $H_{E_1}^N$ and $H_{E_{i+j}}^N$ are from $[H_E^N; H_E^N]$, which is the concatenation of $H_E^N$ and $H_E^N$; $W_{j+1}$ is a span width embedding with fixed size, which is trained during model training.

$E_s$ first passes through a FFN, then is fed into $\text{softmax}$, which yields a posterior on the space of pre-defined entity type size.

$$\hat{y}^s = \text{softmax}(E_s W^s + b^s)$$

Where $W^s$ and $b^s$ are trainable FFN parameters. The training objective is to minimize the cross-entropy loss.

$$\mathcal{L}_E = -\frac{1}{M} \sum_{i=1}^{M} y_i^s \log \hat{y}_i^s$$

Where $y_i^s$ is the one-hot vector of gold span type; $M$ is the number of span instances.

**Decoder for span-based RE.** We first formulate an arbitrary span pair from $S$: $r = \langle s_1, s_2 \rangle$, where $s_1$ and $s_2$ are two text spans. Then we obtain relation representation by concatenation manner.

$$E_r = [E_{s_1}; E_{s_2}; C_r]$$

Where $E_{s_1}$ and $E_{s_2}$ are semantic representations of $s_1$ and $s_2$. It is worth noting that we obtain $E_{s_1}$ and $E_{s_2}$ with $[H_R^N; H_L^N]$ in the same way as in the NER decoder. Following (Eberts and Ulges, 2019), $C_r$ is the semantic representation of relation context, which is obtained with $[H_R^N; H_L^N]$ as well.

$E_r$ first passes through a FFN, then is fed into $\text{sigmoid}$, which yields probability distributions on the space of pre-defined relation type size.

$$\hat{y}^r = \sigma(E_r W^r + b^r)$$

Where $W^r$ and $b^r$ are trainable FFN parameters. Given a confidence threshold $\alpha$, any relation with a score $\geq \alpha$ is considered activated. If none is activated, the model assumes that the span pair holds no pre-defined relation. The training objective is to minimize the binary cross-entropy loss.

$$\mathcal{L}_R = -\frac{1}{M} \sum_{i=1}^{M} (y_i^r \log \hat{y}_i^r + (1 - y_i^r) \log (1 - \hat{y}_i^r))$$

Where $y_i^r$ is the one-hot vector of gold relation type for span pair; $M$ is the number of span pair instances.

Finally, we optimize the following joint objective function during model training.

$$\mathcal{L}_\text{joint}(W; \theta) = \mathcal{L}_L + \mathcal{L}_E + \mathcal{L}_R$$
Figure 4: An example of overlapping entities from ADE, tagged by the extended BIO tagging scheme.

4 Experiments

4.1 Experimental Setup

Datasets. We evaluate our model on ACE05 (Doddington et al., 2004), CoNLL04 (Roth and Yih, 2004) and ADE (Gurulingappa et al., 2012). For ACE05, we use the same entity and relation types, data splits, and pre-processing as (Luan et al., 2019; Wang and Lu, 2020); for CoNLL04, we use the same train-test split as (Zhao et al., 2020; Wang and Lu, 2020); for ADE, we maintain two dataset versions following (Eberts and Ulges, 2019; Wang and Lu, 2020), one is the full ADE dataset with 119 instances that contain overlapping entity, the other without these instances.

Extended BIO tagging scheme. Aiming to make STSN can extract the overlapping entities from the full ADE dataset, we extend the BIO tagging scheme. We first give two term definitions:

- **two-fold overlapping entities** is a pair of overlapping entities that the overlapping tokens are only contained in the two entities.
- **preceding entity** is distinguished by entity head location, while if two entities have the same head location, the entity with longer length is chosen as the preceding entity.

As Figure 4 shows, “Codeine” and “Codeine intoxication” are two-fold overlapping entities, and “Codeine intoxication” is the preceding entity.

Detailed tagging rule is that we first tag the preceding entity with BIO tagging scheme; then for the overlapping entity, we append its BIO labels to existing labels, separated by “/”. For example, we tag the overlapping “Codeine” with “B-AE/B-DRUG”.

As all overlapping entities in the full ADE dataset are two-fold, we tag the dataset with the extended BIO tagging scheme. We first give two term definitions:

Evaluation measures. We use the F1 measure to evaluate model performance. For NER, a predicted entity is considered correct if both its type and boundaries (span head for ACE05) match ground truth. For RE, we adopt two evaluation measures: a predicted relation is considered correct if its relation type and boundaries of the two entities match ground truth (denoted as RE); while RE+ needs both relation type and the two entities all match ground truth. More discussion of the evaluation settings can be found in (Wang and Lu, 2020).

Implementation details. For all datasets, we build STSN by stacking 4 attention layers in depth, and evaluate it upon bert-base-cased (Devlin et al., 2019) and albert-xxlarge-v1 (Lan et al., 2019) with a single NVIDIA RTX 3090 GPU. We optimize STSN using AdamW for 100 epochs with a learning rate of 5e-5, a linear scheduler with a warmup ratio of 0.1 and a weight decay of 10-2. We set the training batch size to 4, dimensions of $W_{j+1}, H_L^N$ to 150, $h$ for multi-head attention to 8, span width threshold to 10 and relation threshold $\alpha$ to 0.4. We adopt negative sampling strategy following (Eberts and Ulges, 2019). For ACE05 and CoNLL04, we run STSN for 20 runs and report the averaged F1 of the top-5 runs. For ADE, we adopt 10-fold cross validation, run each fold for 20 runs and report the averaged F1 of the top-5 runs.

4.2 Main Results

Table 1 and Table 2 compare performances of STSN with previous optimal results. We report the F1 scores for a fair comparison with prior work. Our BERT-based model significantly outperforms all previous work including models built upon ALBERT, where our model performances are further improved by using ALBERT. For NER, our best model delivers absolute F1 gains of +1.7, +1.5 (micro)/+2.7 (macro), +1.9 on ACE05, CoNLL04 and ADE(without overlap) respectively, while better ones for RE, by +3.5 (RE)/+3.7 (RE+), +2.6 (micro)/+2.9 (macro) and +4.2 respectively. All these overwhelming gains demonstrate the effectiveness of leveraging token label information in span-based NER and RE, as well as the bidirectional information interactions between the two tasks.

We evaluate STSN for extracting overlapping entity on the full ADE dataset. Experimental results are shown in Table 2, marked by ♦. Compared to (Eberts and Ulges, 2019), our model delivers overwhelming performance gains. Specifically, on NER and RE, our BERT-based model delivers absolute F1 gains of +1.7 and +4.6, while our ALBERT-based model delivers +2.6 and +5.7. These gains
Table 1: Main results on ACE05 using micro-averaged F1. ⊥: LSTM + ELMo; †: bert-base-cased (or -uncased); ‡: albert-xxlarge-v1.

| Model                | NER | RE | RE+ |
|----------------------|-----|----|-----|
| Li and Ji (2014)     | 80.8| 52.1| 49.5|
| Miwa et al. (2016)   | 83.4| -  | 55.6|
| Katiyar et al. (2017)| 82.6| 55.9| 53.6|
| Sun et al. (2018)    | 83.6| -  | 59.6|
| Li et al. (2019)     | 84.8| -  | 60.2|
| Dixit and Al (2019)  | 86.0| 62.8| -   |
| Luan et al. (2019)   | 88.4| 63.2| -   |
| Wadden et al. (2019) | 88.6| 63.4| -   |
| Wang et al. (2018)   | 87.2| 66.7| -   |
| Lin et al. (2020)    | 88.8| 67.5|     |
| Wang and Lu (2020)   | 89.5| 67.6| 64.3|
| Ji et al. (2020)     | 89.6| -  | 65.2|
| ours †               | 90.2| 68.1| 66.9|
| ours ‡               | 91.3| 71.1| 68.9|

Table 2: Main results on CoNLL04 and ADE. △: micro-averaged F1; ▲: macro-averaged F1; ♠: with overlap; ⊥: LSTM + ELMo; †: bert-base-cased (or -uncased); ‡: albert-xxlarge-v1.

| Model                | NER | RE | RE+ |
|----------------------|-----|----|-----|
| Li et al. (2016)     | 79.5| 63.4| -   |
| Li et al. (2017)     | 84.6| 71.4|     |
| Bekoulis et al. (2018)| 86.4| 74.6|     |
| Eberts et al. (2019) | 89.3| 79.2|     |
| Eberts et al. (2019) | ▲  | 89.3| 78.8|     |
| Wang and Lu (2020)   | 89.7| 80.1|     |
| Zhao et al. (2020)   | 89.4| 81.1|     |
| Ji et al. (2020)     | 90.6| 80.7|     |
| ours ▲               | 91.4| 83.2|     |
| ours ▲               | 92.5| 84.9|     |
| ours ▲               | 91.0| 83.4|     |
| ours ▲               | 91.9| 84.5|     |

validate the effectiveness of both the proposed extended BIO tagging scheme and STSN.

4.3 Analysis
Following established line of work (Eberts and Ulges, 2019; Zhao et al., 2020), we inspect detailed model performance in two aspects by taking SpERT (Eberts and Ulges, 2019) as baseline. For fair comparison, we utilize the BERT-based STSN.

4.3.1 Performance against Entity Length
Figure 5 shows NER performance comparisons of the baseline and STSN under different entity distances on the ACE05 dev set. We partition entity lengths, which is restricted by span width threshold, into 1-2, 3-4, 5-6, 7-8, 9-10. We can observe that STSN consistently outperforms the baseline under all length intervals. Moreover, absolute F1 gains achieved by STSN are further enhanced when entity length increases. In particular, STSN obtains 13.7 and 20.5 absolute F1 gains when entity length is 7-8 and 9-10 respectively, demonstrating that STSN is more effective in terms of long entities.

4.3.2 Performance against Sentence Length
We analyze performances of the baseline and STSN under different sentence lengths on the ACE05 dev set. As Figure 6 shows, we partition the sentence length into 0-19, 20-34, 35-49, ≥50. We can observe that STSN performs way better than the baseline under all sentence lengths. Moreover,
4.4 Ablation Study

We conduct ablation studies on the BERT-based STSN, and use the ACE05 dev set to report ablation results.

**Ablations of attention layers.** We conduct ablations of attention layers by deep stacking different amounts of attention layers in STSN. Table 3 shows ablation results, from which we can conclude that: (1) the model with four stacked layers performs the best; (2) the model consists of one attention layer performs the worst, due to that one layer cannot fully inject token label information into semantic representations for span-based joint extraction; (3) as the model depth increases, model performance first significantly increases and then slightly decreases. This is because that deep models make it easier to fully inject information, while much deeper models tend to inject more noise, which imposes negative impacts on model performance.

**Ablations of model components.** Table 4 reports ablation results, where (1) -LabelEmbedding denotes ablation token label embeddings, which is realized by removing \( H^{N}_L \) from decoders for span-based NER and RE; (2) -E&R-L-A denotes ablating the bidirectional information interactions between span-based NER and RE, which is realized by making E&R-L-A take \( H_L \) as query, key and value respectively in all stacked attention layers; (3) -AttentionLayer denotes ablating all stacked attention layers, where \( \hat{E}_S \) is directly projected into \( H^{N}_N, H^{N}_E \) and \( H^{N}_R \).

Ablation results show that: (1) token label embeddings impose minor positive impacts on model performance, by delivering +0.4 and +0.5 absolute F1 gains on NER and RE respectively; (2) bidirectional information interactions significantly improve model performance, by delivering +0.8 and +2.2 absolute F1 gains on NER and RE respectively; (3) stacked attention layers boost model performance, delivering +2.0 and +4.2 absolute F1 gains on NER and RE respectively.

Reasons can be summarized as that for span-based NER and RE: (1) the deep stacked attention layers can fully inject token label information into semantic representations for them, which greatly enriches their semantics. While compared to above deep fusion way, shallow concatenation way achieved by concatenating token label embeddings plays a negligible role in enriching their semantics; (2) the bidirectional information interactions between the two tasks can greatly enrich their semantics, by fully leveraging task-specific information of each other.

5 Conclusion

In this paper, we propose the Sequence Tagging enhanced Span-based Network (STSN) for joint entity and relation extraction. By adopting a deep stacked neural architecture composed of three basic attention units, STSN can leverage token BIO label information in span-based joint entity and relation extraction. Moreover, the deep neural architecture realizes bidirectional information interactions between span-based NER and RE, which greatly promotes information interactions. Furthermore, we extend the BIO tagging scheme to make STSN can extract overlapping entity. Experiments on three benchmark datasets show that our model overwhelmingly outperforms other competing approaches, creating new state-of-the-art results.
References

Giannis Bekoulis, Johannes Deleu, Thomas Demeester, and Chris Deveder. 2018. Joint entity recognition and relation extraction as a multi-head selection problem. *CoRR*, abs/1804.07847.

Leyang Cui and Yue Zhang. 2019. Hierarchically-refined label attention network for sequence labeling. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 4115–4128, Hong Kong, China. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Kalpit Dixit and Yaser Al-Onaizan. 2019. Span-level model for relation extraction. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5308–5314, Florence, Italy. Association for Computational Linguistics.

George Doddington, Alexis Mitchell, Mark Przybocki, Lance Ramshaw, Stephanie Strassel, and Ralph Weischedel. 2004. The automatic content extraction (ACE) program – tasks, data, and evaluation. In *Proceedings of the Fourth International Conference on Language Resources and Evaluation (LREC’04)*, Lisbon, Portugal. European Language Resources Association (ELRA).

Markus Eberts and Adrian Ulges. 2019. Span-based joint entity and relation extraction with transformer pre-training. *arXiv preprint arXiv:1909.07755*.

Harsha Gurulingappa, Abdul Mateen Rajput, and Angus Roberts. 2012. Development of a benchmark corpus to support the automatic extraction of drug-related adverse effects from medical case reports. *J. Biomed. Informatics*, 45(5):885–892.

Bin Ji, Jie Yu, Shasha Li, Jun Ma, Qingbo Wu, Yusong Tan, and Huijun Liu. 2020. Span-based joint entity and relation extraction with attention-based span-specific and contextual semantic representations. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 88–99.

Arzoo Katiyar and Claire Cardie. 2017. Going out on a limb: Joint extraction of entity mentions and relations without dependency trees. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 917–928, Vancouver, Canada. Association for Computational Linguistics.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. ALBERT: A lite BERT for self-supervised learning of language representations. *CoRR*, abs/1909.11942.

Kenton Lee, Luheng He, Mike Lewis, and Luke Zettlemoyer. 2017. End-to-end neural coreference resolution. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 188–197, Copenhagen, Denmark. Association for Computational Linguistics.

Fei Li, Meishan Zhang, Guohong Fu, and Donghong Ji. 2017. A neural joint model for entity and relation extraction from biomedical text. *BMC bioinformatics*, 18(1):1–11.

Fei Li, Yue Zhang, Meishan Zhang, and Donghong Ji. 2016. Joint models for extracting adverse drug events from biomedical text. In *IJCAI*, volume 2016, pages 2838–2844.

Qi Li and Heng Ji. 2014. Incremental joint extraction of entity mentions and relations. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 402–412, Baltimore, Maryland. Association for Computational Linguistics.

Xiaoya Li, Fan Yin, Zijun Sun, Xiyao Li, Arianna Yuan, Duo Chai, Mingxin Zhou, and Jiwei Li. 2019. Entity-relation extraction as multi-turn question answering. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1340–1350, Florence, Italy. Association for Computational Linguistics.

Ying Lin, Heng Ji, Fei Huang, and Lingfei Wu. 2020. A joint neural model for information extraction with global features. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7999–8009, Online. Association for Computational Linguistics.

Yi Luan, Luheng He, Mari Ostendorf, and Hannaneh Hajishirzi. 2018. Multi-task identification of entities, relations, and coreference for scientific knowledge graph construction. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3219–3232, Brussels, Belgium. Association for Computational Linguistics.

Yi Luan, Dave Wadden, Luheng He, Amy Shah, Mari Ostendorf, and Hannaneh Hajishirzi. 2019. A general framework for information extraction using dynamic span graphs. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 3036–3046, Minneapolis, Minnesota. Association for Computational Linguistics.

Makoto Miwa and Mohit Bansal. 2016. End-to-end relation extraction using LSTMs on sequences and tree
structures. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1105–1116, Berlin, Germany. Association for Computational Linguistics.

Makoto Miwa and Yutaka Sasaki. 2014. Modeling joint entity and relation extraction with table representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1858–1869, Doha, Qatar. Association for Computational Linguistics.

Dat Quoc Nguyen and Karin Verspoor. 2019. End-to-end neural relation extraction using deep biaffine attention. In European Conference on Information Retrieval, pages 729–738. Springer.

Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 2227–2237, New Orleans, Louisiana. Association for Computational Linguistics.

Dan Roth and Wen-tau Yih. 2004. A linear programming formulation for global inference in natural language tasks. In Proceedings of the Eighth Conference on Computational Natural Language Learning (CoNLL-2004) at HLT-NAACL 2004, pages 1–8, Boston, Massachusetts, USA. Association for Computational Linguistics.

Changzhi Sun, Yuanbin Wu, Man Lan, Shiliang Sun, Wenting Wang, Kuang-Chih Lee, and Kewen Wu. 2018. Extracting entities and relations with joint minimum risk training. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2256–2265, Brussels, Belgium. Association for Computational Linguistics.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008.

David Wadden, Ulme Wennberg, Yi Luan, and Hannaneh Hajishirzi. 2019. Entity, relation, and event extraction with contextualized span representations. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5784–5789, Hong Kong, China. Association for Computational Linguistics.

Guoyin Wang, Chunyuan Li, Wenlin Wang, Yizhe Zhang, Dinghan Shen, Xinyuan Zhang, Ricardo Henao, and Lawrence Carin. 2018. Joint embedding of words and labels for text classification. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 2321–2331, Melbourne, Australia. Association for Computational Linguistics.

Jue Wang and Wei Lu. 2020. Two are better than one: Joint entity and relation extraction with table-sequence encoders. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1706–1721, Online. Association for Computational Linguistics.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, and Mohammad Norouzi. 2016. Google’s neural machine translation system: Bridging the gap between human and machine translation. CoRR, abs/1609.08144.

Wei Ye, Bo Li, Rui Xie, Zhonghao Sheng, Long Chen, and Shikun Zhang. 2019. Exploiting entity BIO tag embeddings and multi-task learning for relation extraction with imbalanced data. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1351–1360, Florence, Italy. Association for Computational Linguistics.

Meishan Zhang, Yue Zhang, and Guohong Fu. 2017. End-to-end neural relation extraction with global optimization. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 1730–1740, Copenhagen, Denmark. Association for Computational Linguistics.

Shan Zhao, Minghao Hu, Zhiping Cai, and Fang Liu. 2020. Modeling dense cross-modal interactions for joint entity-relation extraction. In Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI-20, pages 4032–4038. International Joint Conferences on Artificial Intelligence Organization. Main track.