

# Named Entity Recognition and Relation Extraction using Enhanced Table Filling by Contextualized Representations

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## Abstract

In this study, a novel method for extracting named entities and relations from unstructured text based on the table representation is presented. By using contextualized word embeddings, the proposed method computes representations for entity mentions and long-range dependencies without complicated hand-crafted features or neural-network architectures. We also adapt a tensor dot-product to predict relation labels all at once without resorting to history-based predictions or search strategies. These advances significantly simplify the model and algorithm for the extraction of named entities and relations. Despite its simplicity, the experimental results demonstrate that the proposed method outperforms the state-of-the-art methods on the CoNLL04 and ACE05 English datasets. We also confirm that the proposed method achieves a comparable performance with the state-of-the-art NER models on the ACE05 datasets when multiple sentences are provided for context aggregation.

## 1 Introduction

Named Entity Recognition (NER) (Nadeau and Sekine, 2007; Ratnov and Roth, 2009) and Relation Extraction (RE) (Zelenko et al., 2003; Zhou et al., 2005) are two major sub-tasks of Information Extraction (IE). Recent studies have reported advantages of solving these two tasks jointly in terms of both efficiency and accuracy (Miwa and Sasaki, 2014; Li and Ji, 2014; Gupta et al., 2016; Miwa and Bansal, 2016; Zhang et al., 2017). Compared with the pipelined approaches (Chan and Roth, 2011), models that jointly extract named entities (NE) and relations can capture dependencies between entities and relations.

Many existing studies cast joint extraction of NER and RE as a table-filling problem, where entity and relation labels are represented as cells in a

single table (Miwa and Sasaki, 2014; Gupta et al., 2016; Zhang et al., 2017). As reported by these studies, table-filling is a promising approach for extracting both NE and relations. However, table-filling approaches require feature engineering and search strategy, which is merely a representation of the label space of NER and RE. Previous work have designed complicated features to encode contexts and long-range dependencies between NE and relations. For example, Miwa and Sasaki (2014) used hand-crafted syntactic features (e.g., the shortest path between two words in the syntactic tree) and Zhang et al. (2017) extracted syntactic information using the encoder of a pre-trained syntactic parser. Authors in Miwa and Sasaki (2014) explore decoding (search) strategies for filling in the table, based on history-based predictions. In addition, they explore six strategies to determine the order of filling for table cells. History-based predictions are also an obstacle for parallelizing label decoding.

To address the aforementioned issues, we present a novel yet simple method for NER and RE by enhancing table-filling approaches. We utilize BERT initialized with pre-trained weights for representing entity mentions and encoding long-range dependencies among entities to simplify feature engineering. Furthermore, the presented model enhances entity representations with span-based features. To reduce the burden of exploring searching strategies, we utilize a tensor dot-product to fill up cells of relation labels in the table all-at-once (instead of cell-by-cell with beam-search). This modification also simplifies the decoding process and improves decoding parallelism, completing RE with matrix and tensor operations.

This work uses two widely used benchmark datasets, namely, CoNLL04 (Roth and Yih, 2004) and ACE05, both in English, for evaluating the models of both NER and RE. Experimental results demonstrate that the proposed method achieves

		Johanson	Smith	lives	in	London
		1	2	3	4	5
		$j$				
Johanson	1	1 B-PER	6 ⊥	6 ⊥	6 ⊥	6 LiveIn
Smith	2		2 L-PER	6 ⊥	6 ⊥	6 LiveIn
lives	3			3 0	6 ⊥	6 ⊥
in	4				4 0	6 ⊥
London	5					5 U-LOC
	$i$					

Figure 1: An example of the upper triangular matrix  $\mathbf{Y}$  and table-filling strategy. The numbers in the cells indicate the order of filling cells (decoding).  $\perp$  indicates a negative relation label (i.e., there exists no relation among the corresponding words).

higher performance than previous state-of-the-art methods, including SpERT (Eberts and Ulges, 2020) and DyGIE++ (Wadden et al., 2019) in addition to the conventional table-filling systems (Miwa and Sasaki, 2014; Zhang et al., 2017). We confirm that the tensor dot-product successfully predict relation labels at once without any special search strategy. Moreover, the proposed method attains comparable performance to the state-of-the-art NER model DyGIE++ when providing multiple sentences as input for context aggregation. The source code is publicly available at [https://github.com/YoumiMa/Enhanced\\_TF](https://github.com/YoumiMa/Enhanced_TF).

## 2 Proposed Method

This study aims to extract NE and relation instances. Given a sequence of words  $w_1 w_2 \dots w_n$  ( $n$  is the number of words in the input), our goal is to extract relation triples in the form of ( $\text{arg0}_{\text{type0}}$ , relation,  $\text{arg1}_{\text{type1}}$ ). Here,  $\text{type0}$  represents the NE type of the mention  $\text{arg0}$ ;  $\text{arg1}$  and  $\text{type1}$  are defined analogously. We define  $\mathcal{E}$  and  $\mathcal{R}$  as label sets of named entities and relations, respectively.

The table representation (Miwa and Sasaki, 2014) is employed for jointly recognizing NEs and relation instances. Formally, we define an  $n \times n$  upper triangular matrix  $\mathbf{Y}$ , where a diagonal element  $\mathbf{Y}_{i,i} \in \mathcal{E}$  ( $1 \leq i \leq n$ ) represents an NE label for

the word  $w_i$ , and an off-diagonal element  $\mathbf{Y}_{i,j} \in \mathcal{R}$  ( $1 \leq i < j \leq n$ ) represents a directed relation label between the words  $w_i$  and  $w_j$ . Following Zhang et al. (2017), we hard-code directions into relation labels  $\mathcal{R}$  to avoid considering the lower triangular part of the table for RE. Our model can be seen as a mapping transforming a sequence of words  $w_1 w_2 \dots w_n$  to an upper triangular matrix  $\mathbf{Y}$ . We denote an NE label as  $y_i = \mathbf{Y}_{i,i}$  for simplicity. Figure 1 illustrates an example of a matrix  $\mathbf{Y}$  for the input sentence, “Johanson Smith lives in London”. Notably, relations are mapped from 1-dimensional word sequences to 2-dimensional matrix  $\mathbf{Y}$  on entity-level. Further, each word inside an entity span is annotated with the corresponding relation label. Take the sentence in Figure 1 as an example, for the NE “Johanson Smith” labeled as PERSON, relation LIVEIN is labeled on both  $\mathbf{Y}_{1,5}$  and  $\mathbf{Y}_{2,5}$  corresponding to “Johanson” and “Smith,” respectively.

This study is based on pre-trained BERT models to leverage contextual information in solving NER and RE. The proposed method stacks layers for NER and RE on the top of a BERT encoder. As illustrated in Figures 2 and 3, our method computes word representations from contextualized embeddings of sub-word tokens obtained by Byte-Pair-Encoding (BPE) (explained in Section 2.1), and performs NER (Section 2.2) and RE (Section 2.3).

### 2.1 Word Representations

BERT tokenizer uses WordPiece to split words (e.g., “Johanson”) into sub-word tokens (e.g., “Johan” and “##son”) with the aid of BPE. This technique is proved to be effective in reducing the vocabulary size and unknown words (Devlin et al., 2019). Since NEs are annotated at word level, we need its representations at word level during both training and predicting.

In this study, we compute a max-pooling of BERT embeddings of sub-word tokens composing the word as its representation<sup>1</sup> (Liu et al., 2019),

$$e_{w_i} = f(e_{t_{i,1}}, e_{t_{i,2}}, \dots, e_{t_{i,s}}). \quad (1)$$

Here, we assume the following: the word  $w_i$  comprises  $s$  sub-word tokens  $t_{i,1}, t_{i,2}, \dots, t_{i,s}$ ;  $e_{w_i}$  and

<sup>1</sup>We examined the performance on the CoNLL04 development set by using (1) embedding of first sub-word token (Devlin et al., 2019); (2) mean-pooling of constituent sub-word tokens; (3) mean-pooling of constituent sub-word tokens and [CLS]; (4) max-pooling of constituent sub-word tokens. Among these, max-pooling worked the best.

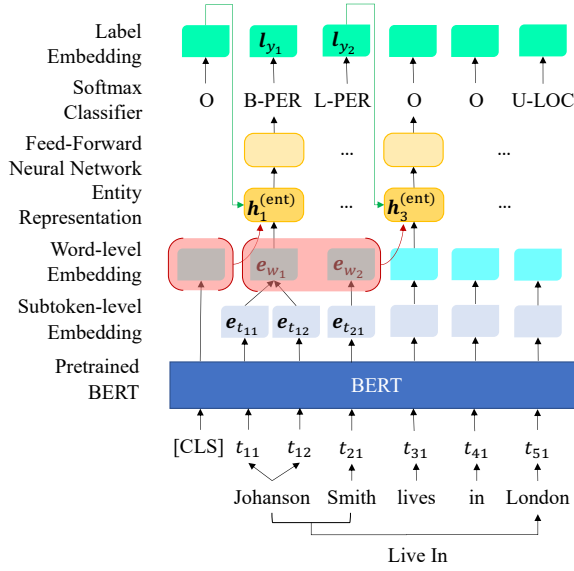


Figure 2: The Named Entity Recognition model. For clarity, we only show the calculation of entity hidden vectors  $h_1^{(ent)}$  and  $h_3^{(ent)}$  for the words “Johanson” and “lives” in detail.

$e_{t_{i,k}}$  are embeddings for the word  $w_i$  and sub-word token  $t_{i,k}$ , respectively; and  $f$  presents a max-pooling operation (henceforth).

## 2.2 Named Entity Recognition

We use the BILOU (begin, inside, last, outside, unit-length) notation for representing spans of NEs (Ratinov and Roth, 2009). We consider NER as a sequential labeling task, where each word  $w_i$  in the input is labeled as  $y_i$  (a diagonal element in  $\mathbf{Y}$ ) in the BILOU notation. In this study, we enhance the existing architecture by using span features at previous timesteps. The use of span features is inspired by Zhang et al. (2017); the authors extracted span representations from bidirectional LSTM cells as features.

Specifically, the model predicts an NE label for the word  $w_i$  based on three features: (1) a representation  $e_{w_i}$  of the word  $w_i$ , (2) embeddings  $l_{y_{i-1}}$  of the label  $y_{i-1}$  at the previous timestep  $i-1$ , and (3) max-pooling of BERT embeddings of the previous NE span appearing at timesteps  $(\text{first}(i-1), \dots, i-1)$ . Here,  $\text{first}(i)$  denotes the timestep where the NE span including word  $i$  starts. For example, when processing the sentence shown in Figure 2, since the phrase “Johanson Smith” is labeled as an NE, we have  $\text{first}(1) = \text{first}(2) = 1$ . Similarly, since “lives” is a single non-entity word, we have  $\text{first}(3) = 3$ . In addition, when the timestep is one ( $i = 1$ ), we assume  $[\text{CLS}]$  as

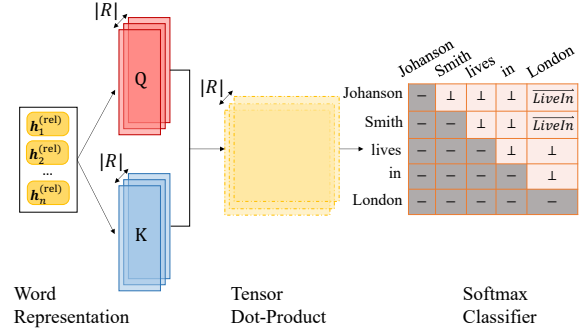


Figure 3: The Relation Extraction model. Relation hidden vectors  $h_i^{(rel)}$  are computed from the NE module. In the right-most table,  $-$  indicates a masked-out cell during both training and predicting.

the previous word and a unit-length outside (O) as the previous label, i.e.,  $y_0 = \text{O}$  and  $w_0 = [\text{CLS}]$ . Following Zhang et al. (2017), when the previous word is labeled O, we assume that the previous span is a unit-length span, i.e.,  $\text{first}(i-1) = i-1$ .

We define the entity representation for predicting the label of current timestep  $i$  as the concatenation of three features described above,

$$h_i^{(ent)} = e_{w_i} \oplus l_{y_{i-1}} \oplus f(e_{w_{\text{first}(i-1)}}, \dots, e_{w_{i-1}}), \quad (2)$$

where  $\oplus$  stands for a vector concatenation.

We apply a fully connected layer followed by a softmax function  $\sigma$  to obtain the probability distribution across all possible NE labels at timestep  $i$ ,

$$\hat{y}_i = \sigma(\mathbf{W}^{(ent)} h_i^{(ent)} + \mathbf{b}^{(ent)}). \quad (3)$$

Here,  $\mathbf{W}^{(ent)}$  and  $\mathbf{b}^{(ent)}$  represent the matrix and the bias vector for a linear transformation. The vector  $\hat{y}_i$  represents the probability distribution over NE labels; we fill the element  $\mathbf{Y}_{i,i} (= y_i)$  with the NE label yielding the highest probability for  $\hat{y}_i$ . Thus, we perform NER by filling up diagonal elements  $\mathbf{Y}_{i,i}$  from  $i = 1$  to  $n$ .

## 2.3 Relation Extraction

We perform RE on top of the BERT encoder and entity spans recognized in Section 2.2. After the NER model fills up all diagonal elements in  $\mathbf{Y}$ , the RE model predicts all off-diagonal elements in  $\mathbf{Y}$ . We adapt a tensor dot-product to score each word pair along with the relation label distribution. The computation is similar to the multi-head self-attention mechanism (Vaswani et al., 2017), but our goal is not to compute attention weights over entity

representations<sup>2</sup>.

Our model utilizes features of entity spans and their NE labels to obtain relation representations for predicting relation labels. Let  $\text{last}(i)$  denote the timestep where the entity span containing the timestep  $i$  ends, analogous to  $\text{first}(i)$  defined in Section 2.2. For instance, for sentence delineated in Figure 2, we have  $\text{last}(1) = \text{last}(2) = 2$ . The entity-span feature  $z_i$  (at timestep  $i$ ) is computed using the representations of the constituent words in the entity span,

$$z_i = f(e_{w_{\text{first}(i)}}, \dots, e_{w_i}, \dots, e_{w_{\text{last}(i)}}). \quad (4)$$

To rephrase,  $z_i$  is the max-pooling across word representations of the entity span starting at  $\text{first}(i)$  and ending at  $\text{last}(i)$ . Embedding of the NE label  $l_{y_i}$  is then used as the entity-label feature at timestep  $i$ . Mathematically, the word representation, i.e., an input to the RE model, is a concatenation of the entity-span and entity-label feature,

$$h_i^{(\text{rel})} = z_i \oplus l_{y_i}. \quad (5)$$

For each possible relation  $r \in \mathcal{R}$ , we apply linear transformations parameterized by two matrices  $W_r^{(q)}, W_r^{(k)} \in \mathbb{R}^{d_{\text{att}} \times d_{\text{rel}}}$  and two bias vectors  $b_r^{(q)}, b_r^{(k)} \in \mathbb{R}^{d_{\text{att}}}$ ,

$$q_{i,r} = W_r^{(q)} h_i^{(\text{rel})} + b_r^{(q)}, \quad (6)$$

$$k_{i,r} = W_r^{(k)} h_i^{(\text{rel})} + b_r^{(k)}, \quad (7)$$

where  $d_{\text{rel}}$  denotes the number of dimensions of  $h_i^{(\text{rel})}$ , and  $d_{\text{att}}$  represents the number of dimensions after the transformations.  $q_{i,r} \in \mathbb{R}^{d_{\text{att}}}$  and  $k_{i,r} \in \mathbb{R}^{d_{\text{att}}}$  are query and key vectors, respectively, for the relation  $r$  at timestep  $i$ . As demonstrated, we map the word representation vector  $h_i^{(\text{rel})}$  into the query and key spaces associated with the relation  $r$ .

After collecting both query and key vectors for all relations  $r \in \mathcal{R}$  at all timesteps  $i \in \{1, \dots, n\}$ , we obtain two tensors  $Q \in \mathbb{R}^{n \times |\mathcal{R}| \times d_{\text{att}}}$  and  $K \in \mathbb{R}^{n \times |\mathcal{R}| \times d_{\text{att}}}$ . Slices of the tensors are,

$$Q_{i,r,:} = q_{i,r} = W_r^{(q)} h_i^{(\text{rel})} + b_r^{(q)}, \quad (8)$$

$$K_{i,r,:} = k_{i,r} = W_r^{(k)} h_i^{(\text{rel})} + b_r^{(k)}. \quad (9)$$

We compute a probability distribution across all possible relations for every combination of  $i$  and

<sup>2</sup>We also tried the deep bi-affine attention mechanism used in Dozat and Manning (2017) and Nguyen and Verspoor (2019). However, we found it sufficient to use the tensor dot-product in the early experiments.

$j$  ( $1 \leq i < j \leq n$ ), which is realized by the dot-product of  $Q$  and  $K$ ,

$$\hat{y}_{i,j} = \sigma(QK^\top)_{i,j,:}. \quad (10)$$

Here,  $(\cdot)_{i,j,:}$  denotes a slice (vector) of the tensor extracting the  $(i, j, *)$  elements. Softmax function  $\sigma$  computes the probability distribution across all relation labels  $\mathcal{R}$ . We fill in the cell  $Y_{i,j}$  with the relation label yielding the highest probability for  $\hat{y}_{i,j}$ . In this way, the RE model predicts relation labels for all pairs of input words at once by computing Equation 10 on the top of NE labels and spans predicted by the NE module.

Meanwhile, we replace Equation 5 with 11 during the training phase,

$$z_i = e_{w_i}. \quad (11)$$

The rationale behind this treatment is that Equation 5 might repeat the same pattern of parameter updates for multiple words within an entity span because of the max-pooling operation. In contrast, Equation 11 promotes different patterns of parameter updates for different words in an entity span<sup>3</sup>.

## 2.4 Training and Predicting

The objective of training is to minimize the sum of cross-entropy losses of NER ( $\mathcal{L}^{(\text{ent})}$ ) and RE ( $\mathcal{L}^{(\text{rel})}$ ),

$$\mathcal{L} = \mathcal{L}^{(\text{ent})} + \mathcal{L}^{(\text{rel})}. \quad (12)$$

The proposed NER model uses ground-truth NE labels and spans at training time, similar to Zhang et al. (2017). We perform a greedy search (from left to right) for predicting a label sequence<sup>4</sup>. Our RE model receives the predicted NE labels and spans from the NER model and then predicts relation labels based on these predictions.

Notably, as shown in Figure 1, if a phrase is labeled as an NE, relations sourcing from or pointing to the phrase will be mapped span-wise to the matrix  $Y$ . The mapping strategy helps us fully update parameters for different words inside an entity span during relation training. During relation prediction, we ignore inconsistency of label predictions among componential words by max-pooling as in Equation 4, which results in the same entity-span feature inside the span.

<sup>3</sup>We explore several combinations. For example, using Equation 5 for both training and predicting phases, we confirmed that the combination: (Equation 5 for prediction and Equation 11 for training), performed the best.

<sup>4</sup>The beam search decoding did not depict a definite performance improvement, which is consistent with the report in Miwa and Bansal (2016).



### 3 Experiment

#### 3.1 Datasets

We assessed the performance for NER and RE of the proposed method on two widely used datasets: CoNLL04 (Roth and Yih, 2004) and ACE05. In addition, the ability of the proposed model to capture cross-sentence dependencies in NER is evaluated on CoNLL03 (Tjong Kim Sang and De Meulder, 2003) and ACE05, which include markers for document boundaries.

**CoNLL04** The dataset defines four entity types and five relation types. We report F1 scores for NER and RE adhering to the conventional evaluation scheme. The experiments followed the setup and data split of Gupta et al. (2016) and Eberts and Ulges (2020), which are similar to those of Miwa and Sasaki (2014) and Zhang et al. (2017).

**ACE05** We used the English corpus that encompasses seven coarse-grained entity types and six coarse-grained relation types. We followed the data splits, pre-processing, and task settings of Li and Ji (2014) and Miwa and Bansal (2016). For evaluating NER, we regarded an entity mention as correct if its label and the headword of its span were identical to the ground truth. For evaluating RE, we report performance values computed by two different criteria to make them comparable with the previous work: ACE05<sup>◇</sup> is indifferent towards incorrect predictions of NE labels, while ACE05<sup>♣</sup> requires NE labels of relation arguments to be correct.

**CoNLL03** The dataset contains four different entity types similar to CoNLL04 (Roth and Yih, 2004). We used this dataset to measure the performance of NER that considers cross-sentence contexts within a document.

#### 3.2 Experimental Settings

The presented model is implemented in PyTorch (Paszke et al., 2019) with HuggingFace Transformer package (Wolf et al., 2019), utilizing BERT<sub>BASE</sub> (cased) (Devlin et al., 2019) as a pre-trained BERT model. We ran all experiments on a single GPU of NVIDIA Tesla V100 (16 GiB). We trained parameters of the NER and RE models as well as those in BERT (fine-tuning) during the training phase, with parameters other than pre-trained BERT initialized with the default initializer. We used the AdamW algorithm implemented in

PyTorch for parameter updates (Loshchilov and Hutter, 2019).

Hyperparameters were tuned on the held-out development set of CoNLL04. Further, we merged the development and training sets of CoNLL04 for the final training and evaluation, following the procedure of Gupta et al. (2016) and Eberts and Ulges (2020). Major hyperparameters are listed in Appendix A. We report mean values of all evaluation metrics following five runs on each dataset throughout the paper.

#### 3.3 Main Results

Table 1 reports the performance of our method on the datasets, along with in several recent studies on joint NER and RE. On the CoNLL04 dataset, the proposed method achieved comparable or slightly better performance in both NER and RE than SpERT, i.e., an existing state-of-the-art (SOTA) model. Another advantage of the proposed method over SpERT is its stability in achieving higher performance. Table 2 reports the standard derivations (SDs) of F1 scores of NER and RE on the CoNLL04 test set achieved by the two models.

In addition, Table 1 indicates that the proposed method outperformed existing work on ACE05. Regardless of the evaluation criteria for RE (ACE05<sup>◇</sup> and ACE05<sup>♣</sup>), F1 scores of the proposed method were approximately 1.0 point higher than those of previous SOTA models (DyGIE++ and Multi-turn QA).

The proposed method ranked second for NER on ACE05 among previous studies, while DyGIE++ portrayed superior performance on NER. However, their method receives document-level contexts as input that make it incomparable with our model, i.e., trained only with sentence-level contexts. In addition, DyGIE++ utilized coreference information from OntoNotes (Pradhan et al., 2012). As we will see in Section 3.6 with Table 5, the proposed method achieved comparable performance to DyGIE++ on NER with document-level context given to the input.

Additionally, a detailed error inspection of both NER and RE is shown in Appendix B. The error inspection aided us in categorizing two significant error types of RE sources, namely, a lack of external knowledge and global constraints.

#### 3.4 Ablation Test

To better understand the significance of our proposed method, we conducted ablation tests. This

Dataset	Model	Entity			Relation		
		P	R	F1	P	R	F1
CoNLL04	Miwa and Sasaki (2014)	81.2	80.2	80.7	76.0	50.9	61.0
	Zhang et al. (2017)	-	-	85.6	-	-	67.8
	Multi-turn QA (Li et al., 2019)	89.0	86.6	87.8	69.2	68.2	68.9
	SpERT (Eberts and Ulges, 2020)	88.3	89.6	88.9	73.0	70.0	71.5
	This work	89.3	91.1	<b>90.2</b>	71.6	71.9	<b>71.8</b>
ACE05 $\diamond$	Li and Ji (2014)	85.2	76.9	80.8	68.9	41.9	52.1
	Dixit and Al-Onaizan (2019)	85.9	86.1	86.0	68.0	58.4	62.8
	DyGIE++ (Wadden et al., 2019)	-	-	<b>88.6</b>	-	-	63.4
	This work	87.2	88.1	87.6	69.0	60.7	<b>64.5</b>
ACE05 $\spadesuit$	Li and Ji (2014)	85.2	76.9	80.8	65.4	39.8	49.5
	SPTree (Miwa and Bansal, 2016)	82.9	83.9	83.4	57.2	54.0	55.6
	Zhang et al. (2017)	-	-	83.6	-	-	57.5
	MRT (Sun et al., 2018)	83.9	83.2	83.6	64.9	55.1	59.6
	Multi-turn QA (Li et al., 2019)	84.7	84.9	84.8	64.8	56.2	60.2
	This work	87.2	88.1	<b>87.6</b>	65.3	57.5	<b>61.1</b>

Table 1: Micro-averaged precision (P), recall (R), and F1 score (F1) on the test sets of CoNLL04 and ACE05. ACE05 $\diamond$  regards a relation prediction to be correct when both the relation label and head regions of two arguments are correct. ACE05 $\spadesuit$  requires that NE labels of arguments are correct in addition to the evaluation criteria of ACE05 $\diamond$ . Notably, NER scores of ACE05 $\diamond$  and ACE05 $\spadesuit$  are comparable because the difference in the evaluation criteria affects RE scores only.

Model	SD	
	NER	RE
SpERT	0.378	0.857
This work	<b>0.187</b>	<b>0.334</b>

Table 2: Standard derivations (SD) of F1 scores of NER and RE on the CoNLL04 test set predicted by SpERT and this work (with five runs).

involves gradual removal of introduced features from the model followed by the measurement of performance drops. Specifically, we ablated features of the label embedding  $\mathbf{l}_{y_{i-1}}$  and the previous span  $f(e_{w_{\text{first}(i-1)}}, \dots, e_{w_{i-1}})$  from Equation 2. Table 3 shows that removing features of previous spans from the model harmed the most, whereas the impact of removing label embeddings at previous timesteps was relatively small. This result validates our assumption that span-level features are beneficial in representing entities for both NER and RE.

### 3.5 Prediction Order

Existing methods for jointly extracting entities and relations with the table-filling approach rely on history-based predictions, i.e., fill up the lower (or upper) triangular part of a table cell-by-cell in a

Model	Entity			Relation		
	P	R	F1	P	R	F1
Full	<b>89.3</b>	<b>91.1</b>	<b>90.2</b>	71.6	<b>71.9</b>	<b>71.8</b>
- Label	<b>89.3</b>	90.6	89.9	<b>72.6</b>	70.7	71.6
- Span	88.7	90.5	89.6	70.6	71.0	70.8
- Both	88.5	90.2	89.3	71.2	70.1	70.7

Table 3: Ablation test of features used in this study on the CoNLL04 test set. “- Label” presents the performance when removing the label embeddings at previous timesteps from the model. “- Span” removes the features of the previous span. “- Both” presents the results when removing both of them.

pre-defined order (Miwa and Sasaki, 2014; Gupta et al., 2016; Zhang et al., 2017). These methods assume that earlier decisions help later decisions, which may involve long-range dependencies. In contrast, our model is free from prediction history for relation labels; it focuses on predicting them at once using a tensor dot-product.

A natural question is whether history-based predictions are useful for the proposed method or not? To find the answer, we designed a variant of the RE model that utilized predicted results of cells to the left of and below a target cell. More specifically, we modified Equation 10 to make use of the embeddings of relation labels at  $(i, j - 1)$  and  $(i + 1, j)$  when predicting a relation label for the element

Order	Entity			Relation		
	P	R	F1	P	R	F1
Once	<b>89.3</b>	<b>91.1</b>	<b>90.2</b>	<b>71.6</b>	<b>71.9</b>	<b>71.8</b>
Seq	88.8	90.3	89.6	68.4	71.7	70.0

Table 4: Performance of the proposed method on the CoNLL04 test set with history-based predictions. “Once” stands for the proposed method that predicts all relation labels at once. “Seq” decides relation labels sequentially so that it can incorporate prediction results of cells to the left of and below a target.

$(i, j)$ , and scheduled predictions in ascending order of distance from the diagonal elements and from left-top to right-bottom.

However, a significant improvement in the performance of the model is not observed even after several fine-tuning efforts. Experimental results on the CoNLL04 test set are shown in Table 4. It is difficult to identify the reason for the experimental results, but the RE model might utilize long-range dependencies from the BERT encoder to make decisions. In addition, the history-based prediction increases the number of parameters and complexity of label predictions, by introducing extra parameters for relation embeddings and additional classifiers. It is potentially beneficial to try several prediction orders as in [Miwa and Sasaki \(2014\)](#), but the experimental results suggest that predicting relation labels at once is sufficient for the proposed method.

### 3.6 Multi-Sentence NER

As described in Section 3.3, the proposed method could not outperform DyGIE++ ([Wadden et al., 2019](#)) on ACE05 NER, because of the unavailability of cross-sentence information such as coreferences. In this subsection, we describe how we eliminated the performance gap by merely providing multiple sentences into the model without modifying the architecture. Specifically, we split a document into segments of multiple sentences such that each segment was not longer than 256 sub-word tokens. This length restriction is introduced due to GPU memory capacity limitations. Assuming that each segment was a sequence of sub-word tokens from multiple sentences, we fed each segment to the model with multiple sentences separated by a special token [SEP], similar to [Devlin et al. \(2019\)](#).

Table 5 shows the performance of NER models on the CoNLL03 and ACE05 with and without multi-sentence inputs. To better investigate the ef-

fectiveness of our model, we use “BERT (our replication)” as the baseline. Our models then equip the BERT encoder with extra modules, as described in Section 2.2. We observe that multi-sentence inputs boosted the performance on both datasets, making our model outperform other models, including DyGIE++ and BERT ([Devlin et al., 2019](#)). By comparing the prediction results, we conclude that multi-sentence input improved predictions for multiple occurrences of the same entity, gathering contexts in different occurrences. Specific shreds of evidence with examples are shown in Appendix C.

Although we cannot apply this technique directly to RE (because the table size is  $\mathcal{O}(n^2)$ ), we tested our RE model in a pipelined fashion by using predictions of NER with multi-sentence input on the ACE05 test set. However, we did not see a performance boost on RE. By analyzing predicted RE instances, we discovered that multi-sentence NER increased the overall performance by capturing coreferences, but it also failed to correctly label some of the NEs essential for RE. The observation emphasizes the importance of improving the design of the RE model and a better approach to combine sentence-level and document-level context during RE.

## 4 Related Work

Early studies formulated the task of jointly extracting entities and relations as a structured prediction with the global features and search algorithms. [Li and Ji \(2014\)](#) presented an incremental algorithm for joint NER and RE with global features and inexact (beam-search) decoding. [Miwa and Sasaki \(2014\)](#) proposed a table representation for entities and relations. Further, it investigated hand-crafted features and complex search heuristics on the table. [Gupta et al. \(2016\)](#) enhanced the table-filling approach by adapting recurrent neural networks (RNNs) to fill cells of a table in a pre-defined sequential order. [Miwa and Bansal \(2016\)](#) explored a shared representation for entities and relations by stacking bidirectional tree-structured and sequential LSTM-RNNs. [Zhang et al. \(2017\)](#) integrated a global optimization technique and syntax-aware word representations. These studies heavily relied on feature engineering (as hand-crafted features or specialized models of deep neural networks) and search/optimization strategies.

Recently, several researchers explored the deep

Dataset	Model	Sentence	Entity		
			P	R	F1
CoNLL03	BERT (reported in <a href="#">Devlin et al. (2019)</a> )	Multi	-	-	92.4
	BERT (our replication)	Single	89.5	89.9	89.7
	BERT (our replication)	Multi	91.3	92.7	92.0
	This work	Single	90.3	90.5	90.4
	This work	Multi	<b>92.0</b>	<b>92.9</b>	<b>92.5</b>
ACE05	DyGIE++ ( <a href="#">Wadden et al., 2019</a> )	Multi	-	-	88.6
	This work	Single	87.2	88.1	87.6
	This work	Multi	<b>88.8</b>	<b>88.6</b>	<b>88.7</b>

Table 5: Results of NER on the CoNLL03 and ACE05 test sets. Values of [Devlin et al. \(2019\)](#) and [Wadden et al. \(2019\)](#) are reported scores. We included a baseline BERT, following the original study settings, which involves each word to be represented by its first sub-word token.

contextualized word representations for the sequential labeling problem. [Liu et al. \(2019\)](#) proposed a deep transition architecture enhanced with the global context and reported improvements on NER and chunking tasks by using contextualized word embeddings. [Straková et al. \(2019\)](#) also demonstrated the effectiveness of the contextualized representations on the architectures for nested named entity recognition, where NE may overlap with multiple labels assigned.

More recently, span-enumeration methods have been a popular approach for jointly extracting entities and relations ([Luan et al., 2019](#); [Wadden et al., 2019](#); [Ebarts and Ulges, 2020](#)). In general, span enumeration methods consider possible entity spans for an input sentence with some criteria (e.g., the maximum number of words), choose likely spans using features extracted from the span candidates. [Luan et al. \(2019\)](#) proposed a general framework of information extraction called DyGIE that can incorporate global information on a dynamic span graph. [Wadden et al. \(2019\)](#) further expanded the model to DyGIE++. The method receives multiple sentences from the same document as input and enumerates candidate spans for relation, coreference, and event identification. To update span representations of entities, they carefully designed strategies for dynamic graph construction and span refinement. [Ebarts and Ulges \(2020\)](#) also proposed an end-to-end RE model for extracting both entities and relations called SpERT. The method bases on pre-trained BERT models and enumerates candidates of entity spans. Using a negative sampling strategy for both NER and RE, the method classifies entity and relation candidates into positive and negative.

We aimed at solving the drawbacks of the table-filling approach, e.g., complicated feature engineering and decoding algorithm. In our approach, feature engineering for NER was removed by using contextualized word representations and span-based features. The proposed method utilized a tensor dot-product for filling in off-diagonal cells at once without using history-based predictions. Although the proposed architecture was different from the span-enumeration based approaches (DyGIE++ and SpERT), the experimental results demonstrated competitive or better performance than the span-enumeration based approaches.

## 5 Conclusion

This paper presented a novel method for extracting NE and relations based on the table representation, making use of contextualized word embeddings for representing entity mentions. We applied tensor dot-product for predicting all the relation labels at once. The experimental results on the CoNLL04 and ACE05 dataset demonstrated that the proposed method outperformed not only the existing table-filling methods but also the SOTA methods based on pre-trained BERT models. We also confirmed that the method achieved comparable performance to the SOTA NER models on the ACE05 when multiple sentences were fed to the model.

In the future, we plan to explore an approach for incorporating global constraints in the RE model, which currently predicts all relation labels independently.



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## Appendix A: Major Hyper-Parameters

This section contains a list of major hyperparameters in our model, as shown in Table 6. For both CoNLL04 and ACE05, we used the same hyperparameters with an exception to batch size, owing to the difference in the data scale. We applied dropout to  $e_{w_i}$  and  $f(e_{w_{\text{first}(i-1)}}, \dots, e_{w_{i-1}})$  in Equation 2 and  $z_i$  in Equation 5.

Parameter	Value
# dims of token embeddings $ e_w $	768
# dims of label embeddings $ l_y $	50
# dims of relation attention $d_{\text{att}}$	20
learning rate (BERT encoder)	$5 \times 10^{-5}$
learning rate (others)	$1 \times 10^{-3}$
dropout rate	0.3
warm-up period	0.2
total number of epochs	30

Table 6: Hyper-parameter settings. We adopted a learning rate scheduler that increased learning rates linearly from 0 to  $5 \times 10^{-5}$  in the warm-up period of  $0.2 \times$  (total number of epochs), and then decreased learning rates using a cosine function.

## Appendix B: Error Inspection

This section contains descriptions for incorrect predictions of the proposed method to delineate future directions for improvement. Table 7 summarizes typical errors of the proposed method found in the CoNLL04 test set.

**Incorrect NE span** Cases where the NER model predicts slightly incorrect spans. Typical errors of this category involve adding/missing a nearby phrase of an NE span. Table 7 (a) is an example where the phrase “on Earth” can be interpreted as a prepositional phrase or a part of a proper noun.

**Incorrect NE type** Cases where the NER model predicts incorrect NE labels for entity mentions. These cases usually occur when an entity can be interpreted with different NE types. Table 7 (b) illustrates that “Charing Cross Hospital” can be categorized as ORGANIZATION if we look at the NE alone, but is actually annotated as LOCATION in the context (indicating the location of the event ‘died’).

**Lack of Knowledge** Cases where the RE model fails to recognize implicit relations. In Table 7 (c), it is not so easy to recognize the relation instance ( $\text{Livingston}_{\text{Loc}}, \text{LocatedIn}, \text{Montana}_{\text{Loc}}$ ) only from the sentence without the knowledge about the entities ‘Livingston’ and ‘Montana’. Fortunately, the RE model could predict the relation instance correctly in this example. However, it is even more difficult to infer the relation instance ( $\text{Livingston}_{\text{Loc}}, \text{LocatedIn}, \text{Rocky Mountains}_{\text{Loc}}$ ) from the text; we are not sure of the inclusion relation between “Rocky Mountain” and ‘Livingston’ without the knowledge about the entities.

(a) Incorrect NE span	
Ground truth	Text of the statement issued by the [Organization of the Oppressed on Earth] <sub>ORG</sub> claiming U. S. Marine Lt. William R. Higgins was hanged.
Prediction	Text of the statement issued by the [Organization of the Oppressed] <sub>ORG</sub> on Earth claiming U. S. Marine Lt. William R. Higgins was hanged.
(b) Incorrect NE type	
Ground truth	Manygate Management said Ogdon died peacefully after going into a coma following his admission to London’s [Charing Cross Hospital] <sub>LOC</sub> Monday for bronchopneumonia.
Prediction	Manygate Management said Ogdon died peacefully after going into a coma following his admission to London’s [Charing Cross Hospital] <sub>ORG</sub> Monday for bronchopneumonia.
(c) Lack of knowledge	
Sentence	High winds blew on the east slopes of the [Rocky Mountains] <sub>LOC</sub> in [Montana] <sub>LOC</sub> , with winds gusting to near 50 mph at [Livingston] <sub>LOC</sub> .
Ground Truth	(Rocky Mountains <sub>LOC</sub> , LocatedIn, Montana <sub>LOC</sub> ) (Livingston <sub>LOC</sub> , LocatedIn, Montana <sub>LOC</sub> ) (Livingston <sub>LOC</sub> , LocatedIn, Rocky Mountains <sub>LOC</sub> )
Prediction	(Rocky Mountains <sub>LOC</sub> , LocatedIn, Montana <sub>LOC</sub> ) (Livingston <sub>LOC</sub> , LocatedIn, Montana <sub>LOC</sub> )
(d) Lack of global constraints	
Sentence	[Soviet] <sub>LOC</sub> Foreign [Eduard A. Shevardnadze] <sub>PEOP</sub> is to visit [China] <sub>LOC</sub> next month to pave the way for the first Chinese - Soviet summit in 30 years ...
Ground Truth	(Eduard A. Shevardnadze <sub>PEOP</sub> , LiveIn, Soviet <sub>LOC</sub> )
Prediction	(Eduard A. Shevardnadze <sub>PEOP</sub> , LiveIn, Soviet <sub>LOC</sub> ) (Eduard A. Shevardnadze <sub>PEOP</sub> , LiveIn, China <sub>LOC</sub> )

Table 7: Typical error cases of the proposed method on the CoNLL04 test set. Cases (a) and (b) are errors caused by the NER model; and Cases (c) and (d) are those caused by the RE model. Each RE case shows the sentence with the NE labels in the first line, followed by relation tuples of the ground truth annotation and the prediction.

**Lack of global constraints** Cases where the RE model could avoid incorrect RE instances with constraints. As shown in Table 7 (d), the model infers that the same person lives in two different places (Soviet and China). the proposed method cannot consider associations between relation predictions explicitly because relation labels are predicted independently of each other.

## Appendix C: Predicted Examples for Multi-Sentence NER

This section contains several typical predicted examples showing the effectiveness of the multi-sentence NER model, as shown in Table 8.

CoNLL03
Location (single), Organization (multi), Organization (gold)
<i>Charleroi</i> ( Belgium ) 75 Estudiantes Madrid ( Spain ) 82 ( 34 - 35 )
Leading scorers: <b>Charleroi</b> - Eric Cleymans 18, Ron Ellis 18, Jacques Stas 14
Person (single), Organization (multi), Organization (gold)
<b>Tambang Timah</b> at \$ 15. 575 in London.
LONDON 1996 - 12 - 07
PT <i>Tambang Timah</i> closed at \$ 15. 575 per GDR in London on Friday.
ACE05
Person (single), Organization (multi), Organization (gold)
<i>North Korea</i> has told American lawmakers it already has nuclear weapons ...
<b>“They</b> admitted to having just about completed the reprocessing of 8, 000 rods,” said ...
Geographical Entity (single), Person (multi), Person (gold)
...today’s <i>Southern voters</i> are “children of Democrats who are not swayed by the same things ...
<b>They</b> certainly are susceptible to the Republican message. ”

Table 8: Typical examples where the proposed NER model showed improvements with multi-sentence input. A **boldface** word presents a target for predicting the NE label, and an *italic* word is a coreference to the boldface word. NE labels shown on top of each example are the prediction from single-sentence input; that from multi-sentence input; and the ground-truth label. We can infer that the model with multi-sentence input made correct predictions, looking at coreferential words.