End-to-End Neural Relation Extraction with Global Optimization

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Abstract

Neural networks have shown promising results for relation extraction. State-of-the-art models cast the task as an end-to-end problem, solved incrementally using a local classifier. Yet previous work using statistical models have demonstrated that global optimization can achieve better performances compared to local classification. We build a globally optimized neural model for end-to-end relation extraction, proposing novel LSTM features in order to better learn context representations. In addition, we present a novel method to integrate syntactic information to facilitate global learning, yet requiring little background on syntactic grammars thus being easy to extend. Experimental results show that our proposed model is highly effective, achieving the best performances on two standard benchmarks.

1 Introduction

Extracting entities (Florian et al., 2006, 2010) and relations (Zhao and Grishman, 2005; Jiang and Zhai, 2007; Sun et al., 2011; Plank and Moschitti, 2013) from unstructured texts have been two central tasks in information extraction (Grishman, 1997; Doddington et al., 2004). Traditional approaches to relation extraction take entity recognition as a predecessor step in a pipeline (Zelenko et al., 2003; Chan and Roth, 2011), predicting relations between given entities.

In recent years, there has been a surge of interest in performing end-to-end relation extraction, jointly recognizing entities and relations given free text inputs (Li and Ji, 2014; Miwa and Sasaki, 2014; Miwa and Bansal, 2016; Gupta et al., 2016). End-to-end learning prevents error propagation in the pipeline approach, and allows cross-task dependencies to be modeled explicitly for entity recognition. As a result, it gives better relation extraction accuracies compared to pipelines.

Miwa and Bansal (2016) were among the first to use neural networks for end-to-end relation extraction, showing highly promising results. In particular, they used bidirectional LSTM (Graves et al., 2013) to learn hidden word representations under a sentential context, and further leveraged tree-structured LSTM (Tai et al., 2015) to encode syntactic information, given the output of a parser. The resulting representations are then used for making local decisions for entity and relation extraction incrementally, leading to much improved results compared with the best statistical model (Li and Ji, 2014). This demonstrates the strength of neural representation learning for end-to-end relation extraction.

On the other hand, Miwa and Bansal (2016)'s model is trained locally, without considering structural correspondences between incremental decisions. This is unlike existing statistical methods, which utilize well-studied structured prediction methods to address the problem (Li and Ji, 2014; Miwa and Sasaki, 2014). As has been commonly understood, learning local decisions for structured prediction can lead to label bias (Lafferty et al., 2001), which prevents globally optimal structures from receiving optimal scores by the model. We address this potential issue by building a structural neural model for end-to-end relation extraction, following a recent line of efforts on globally optimized models for neural structured prediction (Zhou et al., 2015; Watanabe and Sumita, 2015; Andor et al., 2016; Wiseman and Rush, 2016).

In particular, we follow Miwa and Sasaki (2014), casting the task as an end-to-end table-filling problem. This is different from the action-based method of Li and Ji (2014), yet has shown to

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be more flexible and accurate (Miwa and Sasaki, 2014). We take a different approach to representation learning, addressing two potential limitations of Miwa and Bansal (2016).

First, Miwa and Bansal (2016) rely on external syntactic parsers for obtaining syntactic information, which is crucial for relation extraction (Culotta and Sorensen, 2004; Zhou et al., 2005; Bunescu and Mooney, 2005; Qian et al., 2008). However, parsing errors can lead to encoding inaccuracies of tree-LSTMs, thereby hurting relation extraction potentially. We take an alternative approach to integrating syntactic information, by taking the hidden LSTM layers of a bi-affine attention parser (Dozat and Manning, 2016) to augment input representations. Pretrained for parsing, such hidden layers contain rich syntactic information on each word, yet do not explicitly represent parsing decisions, thereby avoiding potential issues caused by incorrect parses.

Our method is also free from a particular syntactic formalism, such as dependency grammar, constituent grammar or combinatory categorial grammar, requiring only hidden representations on word that contain syntactic information. In contrast, the method of Miwa and Bansal (2016) must consider tree LSTM formulations that are specific to grammar formalisms, which can be structurally different (Tai et al., 2015).

Second, Miwa and Bansal (2016) did not explicitly learn the representation of segments when predicting entity boundaries or making relation classification decisions, which can be intuitively highly useful, and has been investigated in several studies (Wang and Chang, 2016; Zhang et al., 2016). We take the LSTM-Minus method of Wang and Chang (2016), modelling a segment as the difference between its last and first LSTM hidden vectors. This method is highly efficient, yet gives as accurate results as compared to more complex neural network structures to model a span of words (Cross and Huang, 2016).

Evaluation on two benchmark datasets shows that our method outperforms previous methods of Miwa and Bansal (2016), Li and Ji (2014) and Miwa and Sasaki (2014), giving the best reported results on both benchmarks. Detailed analysis shows that our integration of syntactic features is as effective as traditional approaches based on discrete parser outputs. We make our code publicly

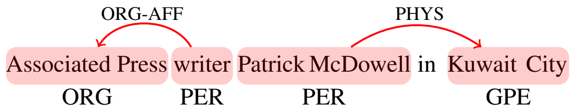


Figure 1: Relation extraction. The example is chosen from the ACE05 dataset, where ORG, PER and GPE denote organization, person and geo-political entities, respectively; ORG-AFF and PHYS denote organization affiliation and physical relations, respectively.

available under Apache License 2.0.[1]

2 Model

2.1 Task Definition

As shown in Figure 1, the goal of relation extraction is to mine relations from raw texts. It consists of two sub-tasks, namely entity detection, which recognizes valid entities, and relation classification, which determines the relation categories over entity pairs. We follow recent studies and recognize entities and relations as one single task.

2.2 Method

We follow Miwa and Sasaki (2014) and Gupta et al. (2016), treating relation extraction as a table-filling problem, performing entity detection and relation classification using a single incremental model, which is similar in spirit to Miwa and Bansal (2016) by performing the task end-to-end.

Formally, given a sentence $w_1 w_2 \cdots w_n$, we maintain a table $T^{n \times n}$, where $T(i, j)$ denotes the relation between w_i and w_j. When $i = j$, $T(i, j)$ denotes an entity boundary label. We map entity words into labels under the BILOU (Begin, Inside, Last, Outside, Unit) scheme, assuming that there are no overlapping entities in one sentence (Li and Ji, 2014; Miwa and Sasaki, 2014; Miwa and Bansal, 2016). Only the upper triangular table is necessary for indicating the relations.

We adopt the close-first left-to-right order (Miwa and Sasaki, 2014) to map the two-dimensional table into a sequence, in order to fill the table incrementally. As shown in Figure 2, first $\{T(i, i)\}$ are filled by growing i, and then the sequence $\{T(i, i+1)\}$ is filled, and then $\{T(i, i+2)\}, \cdots, \{T(i, i+n)\}$ are filled incrementally, until the table is fully annotated.

During the table-filling process, we take two label sets for entity detection ($i = j$) and relation

[1]https://github.com/zhangmeishan/NNRelationExtraction

	Associated	Press	writer	Patrick	McDowell	in	Kuwait	City
Associated	1 B-ORG	9 ⊥	16 ⊥	22 ⊥	27 ⊥	31 ⊥	34 ⊥	36 ⊥
Press		2 L-ORG	10 $\overleftarrow{\text{ORG-AFF}}$	17 ⊥	23 ⊥	28 ⊥	32 ⊥	35 ⊥
writer			3 U-PER	11 ⊥	18 ⊥	24 ⊥	29 ⊥	33 ⊥
Patrick				4 B-PER	12 ⊥	19 ⊥	25 ⊥	30 ⊥
McDowell					5 L-PER	13 ⊥	20 ⊥	26 $\overrightarrow{\text{PHYS}}$
in						6 O	14 ⊥	21 ⊥
Kuwait							7 B-GPE	15 ⊥
City								8 L-GPE

Figure 2: Table-filling example, where numbers indicate the filling order.

classification ($i < j$), respectively. The labels for entity detection include {B-*, I-*, L-*, O, U-* }, where * denotes the entity type, and the labels for relation classification are { $\overrightarrow{*}$, $\overleftarrow{*}$, $\perp$}, where * denotes the relation category and $\perp$ denotes a NULL relation.[2]

At each step, given a partially-filled table T, we determine the most suitable label l for the next step using a scoring function:

$$\text{score}(T, l) = W_l h_T, \quad (1)$$

where W_l is a model parameter and h_T is the vector representation of T. Based on the function, we aim to find the best label sequence $l_1 \cdots l_m$, where $m = \frac{n(n+1)}{2}$, and the resulting sequence of partially-filled tables is $T_0 T_1 \cdots T_m$, where $T_i = \text{FILL}(T_{i-1}, l_i)$, and T_0 is an empty table. Different from previous work, we investigate a structural model that is optimized for the label sequence $l_1 \cdots l_m$ globally, rather than for each l_i locally.

2.3 Representation Learning

At the ith step, we determine the label l_i of the next table slot based on the current hypothesis T_{i-1}. Following Miwa and Bansal (2016), we use a neural network to learn the vector representation of T_{i-1}, and then use Equation 1 to rank candidate next labels. There are two types of input features, including the word sequence $w_1 w_2 \cdots w_n$, and the readily filled label sequence $l_1 l_2 \cdots l_{i-1}$. We build a neural network to represent T_{i-1}.

2.3.1 Word Representation

Shown in Figure 3, we represent each word w_i by a vector h_i^w using its word form, POS tag and characters. Two different forms of embeddings are used based on the word form, one being obtained by using a randomly initialized look-up table E_w,

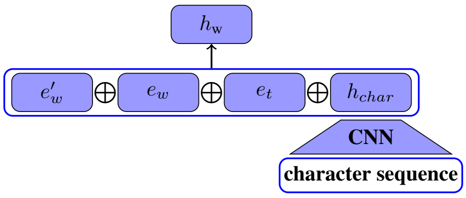


Figure 3: Word representations.

tuned during training and represented by e_w, and the other being a pre-trained external word embedding from E'_w, which is fixed and represented by e'_w.[3] For a POS tag t, its embedding e_t is obtained from a look-up table E_t similar to E_w.

The above two components have also been used by Miwa and Bansal (2016). We further enhance the word representation by using its character sequence (Ballesteros et al., 2015; Lample et al., 2016), taking a convolution neural network (CNN) to derive a character-based word representation h_{char}, which has been demonstrated effective for several NLP tasks (dos Santos and Gatti, 2014). We obtain the final h_i^w based on a non-linear feed-forward layer on $e'_w \oplus e_w \oplus e_t \oplus h_{char}$, where $\oplus$ denotes concatenation.

2.3.2 Label Representation

In addition to the word sequence, the history label sequence $l_1 l_2 \cdots l_{i-1}$, and especially the labels representing detected entities, are also useful disambiguation. For example, the previous entity boundary label can be helpful to deciding the boundary label of the current word. During relation classification, the types of the entities involved can indicate the relation category between them. We exploit the diagonal label sequence of partial table T, which denotes entity boundaries, to enhance the representation learning. A word's entity boundary label embedding e_l is obtained by

[2] We remove the illegal table-filling labels during decoding for training and testing. For example, $T(i, j)$ must be $\perp$ if $T(i, i)$ or $T(j, j)$ equals O.

[3] We use the set of pre-trained glove word embeddings available at http://nlp.stanford.edu/data/glove.6B.zip as external word embeddings.

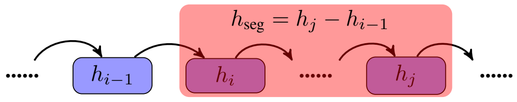


Figure 4: Segment representation.

using a randomly initialized looking-up table E_l.

2.3.3 LSTM Features

We follow Miwa and Bansal (2016), learning global context representations using LSTMs. Three *basic* LSTM structures are used: a left-to-right word LSTM ($\overrightarrow{\text{LSTM}}_w$), a right-to-left word LSTM ($\overleftarrow{\text{LSTM}}_w$) and a left-to-right entity boundary label LSTM ($\overrightarrow{\text{LSTM}}_e$). Each LSTM derives a sequence of hidden vectors for inputs. For example, for $w_1 w_2 \cdots w_n$, $\overrightarrow{\text{LSTM}}_w$ gives $h_1^{w,\rightarrow} h_2^{w,\rightarrow} \cdots h_n^{w,\rightarrow}$.

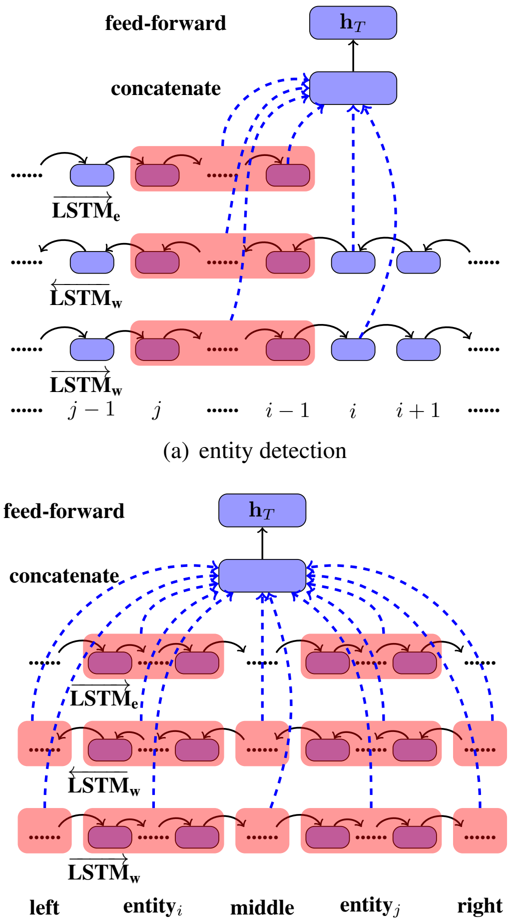
Different from Miwa and Bansal (2016), who use the output hidden vectors $\{h_i\}$ of LSTMs to represent words, we exploit *segment* representations as well. In particular, for a segment of text $[i, j]$, the representation is computed by using LSTM-Minus (Wang and Chang, 2016), shown by Figure 4, where $h_j - h_{i-1}$ in a left-to-right LSTM and $h_i - h_{j+1}$ in a right-to-left LSTM are used to represent the segment $[i, j]$. The segment representations can reflect entities in a sentence, and thus can be potentially useful for both entity detection and relation extraction.

2.3.4 Feature Representation

We use separate feature representations for entity detection and relation classification, both of which are extracted from the above three LSTM structures. In particular, we first extract a set of base neural features, and then concatenate them and feed them into a non-linear neural layer for entity detection and relation classification, respectively. Figure 5 shows the overall representation.

[Entity Detection] Figure 5(a) shows the feature representation for the entity detection. First, we extract six feature vectors from the three basic LSTMs, three of which are word features, namely $h_i^{w,\rightarrow}$, $h_i^{w,\leftarrow}$ and $h_{i-1}^{e,\rightarrow}$, and the remaining are segment features, namely $h_{[j,i-1]}^{w,\rightarrow}$, $h_{[j,i-1]}^{w,\leftarrow}$ and $h_{[j,i-1]}^{e,\rightarrow}$, where j denotes the start position of the previous entity.[4] The segment features are computed dynamically from the partial outputs of entity detection, according to the boundaries of the lastly-

[4]The non-entity word is treated as a special unit entity to extract segmental features.



(a) entity detection

(b) relation classification

Figure 5: Feature representation.

formed entity during the decoding. The six vectors are concatenated and then fed into a non-linear layer for entity detection.

[Relation Classification] Figure 5(b) shows the feature representation for relation classification. Similar to entity detection, we extract a set of features from the basic LSTMs ($\overrightarrow{\text{LSTM}}_w$, $\overleftarrow{\text{LSTM}}_w$ and $\overrightarrow{\text{LSTM}}_e$), and then concatenate them for a non-linear classification layer. The differences between relation classification with entity detection lie in the range of hidden layers from LSTMs. For relation classification between i and j, we split each LSTM into five segments according to the two entities ended with i and j. Formally, let $[s(i), i]$ and $[s(j), j]$ denote the two entities above, where $s(\cdot)$ denotes the start position of an entity, the resulted segments are $[0, s(i)-1]$ (i.e., **left**, in Figure 5(b)), $[s(i), i]$ (i.e., **entity**$_i$), $[i+1, s(j)-1]$ (i.e., **middle**), $[s(j), j]$ (i.e., **entity**$_j$) and $[j+1, n]$ (i.e., **right**), respectively. For the word LSTMs, we extract all five segment features, while the en-

Models	Encoder	LAS
S-LSTM (2015)	1-Layer LSTM	90.9
K&G (2016)	2-Layer Bi-LSTM	91.9
D&M (2016)	4-Layer Bi-LSTM	**93.8**

Table 1: Encoder structures and performances of three state-of-the-art dependency parsers, where S-LSTM (2015) refers to Dyer et al. (2015), K&G (2016) refers to the best parser of Kiperwasser and Goldberg (2016), D&M (2016) refers to Dozat and Manning (2016), and LAS (labeled attachment score) is the major evaluation metric.

tity label LSTM, we only use the segment features of $\textbf{entity}_i$ and $\textbf{entity}_j$.

2.3.5 Syntactic Features

Previous work has shown that syntactic features are useful for relation extraction (Zhou et al., 2005). For example, the shortest dependency path has been used by several relation extraction models (Bunescu and Mooney, 2005; Miwa and Bansal, 2016). Here we propose a novel method to integrate syntax, without need for prior knowledge on concrete syntactic structures.

In particular, we take state-of-the-art syntactic parsers that use encoder-decoder neural models (Buys and Blunsom, 2015; Kiperwasser and Goldberg, 2016), where the encoder represents the syntactic features of the input sentences. For example, LSTM hidden states over the input word/tag sequences has been used frequently as syntactic features (Kiperwasser and Goldberg, 2016). Such features represent input words with syntactic information. The parser decoder also leverages partially-parsed results, such as features from partial syntactic trees, although we do not use explicit output features. Table 1 shows the encoder structures of three state-of-the-art dependency parsers.

Our method is to leverage trained syntactic parsers, dumping the encoder feature representations given our inputs, using them directly as part of input embeddings in our proposed model. Denoting the dumped syntactic features on each word as $h_1^{\text{syn}} h_2^{\text{syn}} \cdots h_n^{\text{syn}}$, we feed them into a non-linear neural layer, and then generate two LSTMs (bi-directional) based on the outputs, namely $\overrightarrow{\text{LSTM}}_{syn}$ and $\overleftarrow{\text{LSTM}}_{syn}$, respectively, augmenting the original three LSTMs into five LSTMs. Features are extracted from the two new LSTMs in the same way as from the basic bi-directional word LSTMs.

In this paper, we exploit the parser of Dozat and Manning (2016), since it achieves the current best performance for dependency parsing. Our method can be easily generalized to other parsers, which are potentially useful for our task as well. For example, we can use a constituent parser in the same way by dumping the implicit encoder features.

Our exploration of syntactic features has two main advantages over the method of Miwa and Bansal (2016), where dependency path LSTMs are used for relation classification. On the one hand, incorrect dependency paths between entity pairs can propagate to relation classification in Miwa and Bansal (2016), because these paths rely on explicit discrete outputs from a syntactic parser. Our method can avoid the problem since we do not compute parser outputs. On the other hand, the computation complexity is largely reduced by using our method since sequential LSTMs are based on inputs only, while the dependency path LSTMs should be computed based on the dynamic entity detection outputs. When beam search is exploited during decoding, increasing number of dependency paths can be used by a surge of entity pairs from beam outputs.

Our method can be extended into neural stacking Wang et al. (2017), by doing back-propagation training of the parser parameters during model training, which are leave for future work.

2.4 Training and Search

2.4.1 Local Optimization

Previous work (Miwa and Bansal, 2016; Gupta et al., 2016) trains model parameters by modeling each step for labeling one input sentence separately. Given a partial table T, its neural representation h_T is first obtained, and then compute the next label scores $\{l_1, l_2, \cdots, l_s\}$ using Equation 1. The output scores are regularized into a probability distribution $\{p_{l_1}, p_{l_2}, \cdots, p_{l_s}\}$ by using a softmax layer. The training objective is to minimize the cross-entropy loss between this output distribution with the gold-standard distribution:

$$\text{loss}(T, l_i^g, \Theta) = -\log p_{l_i^g}, \quad (2)$$

where l_i^g is the gold-standard next label for T, and Θ is the set of all model parameters. We refer this training method as *local optimization*, because it maximizes the score of the gold-standard label at each step locally.

Algorithm 1 Beam-search.

```
agenda ← { (empty table, score=0.0) }
for i in 1 ··· max-step
    next_scored_tables ← { }
    for scored_table in agenda
        labels ← NEXTLABELS(scored_table)
        for next_label in labels
            new ← FILL(scored_table, next_label)
            ADDITEM(next_scored_tables, new)
    agenda ← TOP-B(next_scored_tables, B)
```

During the decoding phase, the greedy search strategy is applied in consistence with the training. At each step, we find the highest-scored label based on the current partial table, before going on to the next step.

2.4.2 Global Optimization

We exploit the global optimization strategy of Zhou et al. (2015) and Andor et al. (2016), maximizing the cumulative score of the gold-standard label sequence for one sentence as a unit. Global optimization has achieved success for several NLP tasks under the neural setting (Zhou et al., 2015; Watanabe and Sumita, 2015). For relation extraction, global learning gives the best performances under the discrete setting (Li and Ji, 2014; Miwa and Sasaki, 2014). We study such models here for neural network models.

Given a label sequence of $l_1 l_2 \cdots l_i$, the score of T_i is defined as follows:

$$\begin{aligned} \text{score}(T_i) &= \sum_{j=0}^{i} \text{score}(T_{j-1}, l_j) \\ &= \text{score}(T_{i-1}) + \text{score}(T_{i-1}, l_i), \end{aligned} \quad (3)$$

where $\text{score}(T_0) = 0$ and $\text{score}(T_{i-1}, l_i)$ is computed by Equation 1. By this definition, we maximize the scores of all gold-standard partial tables.

Again cross-entropy loss is used to perform model updates. At each step i, the objective function is defined by:

$$\begin{aligned} \text{loss}(x, T_i^g, \Theta) &= -\log p_{T_i^g} \\ &= -\log \frac{\text{score}(T_i^g)}{\sum_{T_i'} \text{score}(T_i')}, \end{aligned} \quad (4)$$

where x denotes the input sentence, T_i^g denotes the gold-standard state at step i, and T_i' are all partial tables that can be reached at step i.

The major challenge is to compute $p_{T_i^g}$, because we cannot traverse all partial tables that are valid at step i, since their count increases exponentially by the step number. We follow Andor et al. (2016), approximating the probability by using beam search and early-update.

Shown in Algorithm 1, we use standard beam search, maintaining the B highest-scored partially-filled tables in an agenda at each step. When each action of table filling is taken, all hypotheses in the agenda are expanded by enumerating the next labels, and the B highest-scored resulting tables are used to replace the agenda for the next step. Search begins with the agenda containing an empty table, and finishes when all cells of the tables in the agenda have been filled. When the beam size is 1, the algorithm is the same as greedy decoding. When the beam size is larger than 1, however, error propagation is alleviated. For training, the same beam search algorithm is applied to training examples, and early-update (Collins and Roark, 2004) is used to fix search errors.

3 Experiments

3.1 Data and Evaluation

We evaluate the proposed model on two datasets, namely the ACE05 data and the corpus of Roth and Yih (2004) (CONLL04), respectively. The ACE05 dataset defines seven coarse-grained entity types and six coarse-grained relation categories, while the CONLL04 dataset defines four entity types and five relation categories.

For the ACE05 dataset, we follow Li and Ji (2014) and Miwa and Bansal (2016), splitting and preprocessing the dataset into training, development and test sets.[5] For the CONLL04 dataset, we follow Miwa and Sasaki (2014) to split the data into training and test corpora, and then divide 10% of the training corpus for development.

We use the micro F1-measure as the major metric to evaluate model performances, treating an entity as correct when its head region and type are both correct,[6] and regard a relation as correct when the argument entities and the relation category are all correct. We exploit pairwise t-test for measuring significance values.

[5] https://github.com/tticoin/LSTM-ER/.

[6] For the ACE05 dataset, the head region is defined by the corpus, and for the CONLL04 dataset, the head region covers the entire scope of an entity.

Network Structure	Size
Word Embedding	200
Tag Embedding	50
Char Embedding	50
Entity Label Embedding	50
Input/Output of Word LSTMs	250
Input/Output of Entity Label LSTMs	100
Table Representation	300

Table 2: Dimension sizes.

Model	Entity F1	Relation F1
baseline	**81.5**	**50.9**
-character	80.9	50.2
-segment (entity detection)	80.2	49.8

Table 3: Feature ablation tests.

3.2 Parameter Tuning

We update all model parameters by back propagation using Adam (Kingma and Ba, 2014) with a learning rate 10^{-3}, using gradient clipping by a max norm 10 and l_2-regularization by a parameter 10^{-5}. The dimension sizes of various vectors in neural network structure are shown in Table 2. All the hyper-parameters are tuned by development experiments. All experiments are conducted using gcc version 4.9.4 (Ubuntu 4.9.4-2ubuntu1 14.04.1), on an Intel(R) Xeon(R) CPU E5-2670 @ 2.60GHz.

Online training is used to learn parameters, traversing over the entire training examples by 300 iterations. We select the best iteration number according to the development results. In particular, we exploit pre-training techniques (Wiseman and Rush, 2016) to learn better model parameters. For the local model, we follow Miwa and Bansal (2016), training parameters only for entity detection during the first 20 iterations. For the global model, we pretrain our model using local optimization for 40 iterations, before conducting beam global optimization.

3.3 Development Experiments

We conduct several development experiments on the ACE05 development dataset.

3.3.1 Feature Ablation Tests

We consider the baseline system with no syntactic features using local training. Compared with Miwa and Bansal (2016), we introduce character-level features, and in addition exploit segmental features for entity detection. Feature ablation experiments are conducted for the two types of features. Table 3 shows the experimental results, which demonstrate that the character-level features and the segment features we use are both useful for relation extraction.

Model	Beam	Relation F1	Speed
Local	1	50.9	**95.6**
Local(+SS)	1	51.2	95.1
Global	1	51.4	95.3
	3	51.8	52.0
	5	**52.6**	36.9

Table 4: Comparisons between local and global models, where SS denotes scheduled sampling, and speed is measured by the number of sentences per second.

3.3.2 Local v.s. Global Training

We study the influence of training strategies for relation extraction without using syntactic features. For the local model, we apply scheduled sampling (Bengio et al., 2015), which has been shown to improve the performance of relation extraction by Miwa and Bansal (2016).

Table 4 shows the results. Scheduled sampling achieves improved F-measure scores for the local model. With the same greedy search strategy, the globally normalized model gives slightly better results than the local model with scheduled sampling. The performance of the global model increases with a larger beam size. When beam size 5 is exploited, we obtain a further gain of 1.2% on the relation F-measure, which is significantly better than our baseline local model with scheduled sampling ($p \approx 10^{-4}$). However, the decoding speed becomes intolerably slow when the beam size increases beyond 5. Thus we exploit a beam size of 5 for global training considering both performance and efficiency.

3.3.3 Syntactic Features

We examine the effectiveness of the proposed implicit syntactic features. Table 5 shows the development results using both local and global optimization. The proposed features improve the relation performances significantly under both settings ($p < 10^{-4}$), demonstrating that our use of syntactic features is highly effective.

We also compare our feature integration method with the traditional methods based on syntactic

Model	Features	Entity F1	Relation F1
Local	all	**81.6**	**53.0**
	-syn	81.5	50.9
Global	all	**81.9**	**54.2**
	-syn	81.6	52.6

Table 5: The influence of syntactic features.

model	ACE05		CONLL04	
	Entity	Relation	Entity	Relation
Our Model	**83.6**	**57.5**	**85.6**	**67.8**
M&B (2016)	83.4	55.6	—	—
L&J (2014)	80.8	49.5	—	—
M&S (2014)	—	—	80.7	61.0

Table 6: Final results on the test datasets.

outputs which Miwa and Bansal (2016) and all previous methods use. We use the same parser of Dozat and Manning (2016), building features on its dependency outputs. We exploit the bi-directional tree LSTM of Teng and Zhang (2016) to extract neural features, and then exploit a non-linear feed-forward neural network to combine the two features. Similarly, we extract segment features but by using max pooling instead over the sequential outputs of the feed-forward layer, since the vector minus is nonsense here. The final relation results are 53.1% and 53.9% for the local and global models, respectively, which have no significantly differences compared with our models. On the other hand, our method is relatively more efficient, and flexible to the grammar formalism.

3.4 Final Results

Table 6 shows the final results on the test datasets of ACE05 and CONLL04. We show several top-performing systems in the table as well, where M&B (2016) refers to Miwa and Bansal (2016), who exploit end-to-end LSTM neural networks with local optimization, and L&J (2014) and M&S (2014) refer to Li and Ji (2014) and Miwa and Sasaki (2014), respectively, which are both globally optimized models using discrete features, giving the top F-scores among statistical models.[7]

Overall, neural models give better performances than statistical models, and global optimization can give improved performances as well. Our final model achieves the best performances on both datasets. Compared with the best reported results, our model gives improvements of 1.9% on ACE05, and 6.8% on CONLL04.

[7] Gupta et al. (2016) proposed a locally optimized model but used a different test dataset from CONLL04 and a different evaluation method, reporting entity and relation F-scores of 93.6% and 72.1%, respectively. Their results are not directly comparable to the results in Table 6. In particular, they regard an entity as correct if at least one token is tagged correctly, which influences the results significantly since multi-word entities accounts for over 50% of all entities.

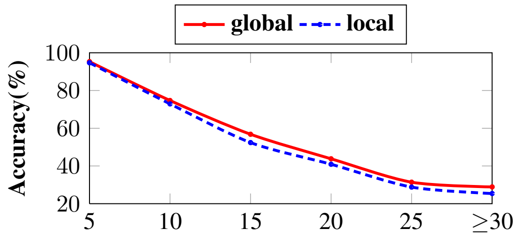


Figure 6: Sentence-level accuracies with respect to sentence length.

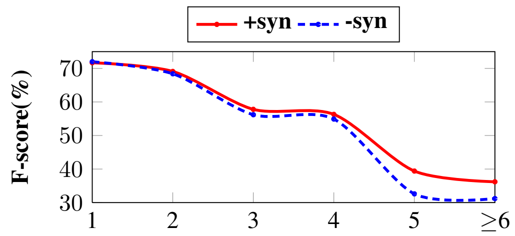


Figure 7: F-scores with respect to the distance between entity pairs.

3.5 Analysis

We conduct analysis on the ACE05 test dataset in order to better understand our models, on its two major contributions, first examining the influences of global optimization, and then studying the gains by using the proposed syntactic features.

Intuitively global optimization should give better accuracies at the sentence level. We verify this by examining the sentence-level accuracies, where one sentence is regarded as correct when all the labels in the resulted table are correct. Figure 6 shows the result, which is consistent with our intuition. The sentence-level accuracies of the globally normalized model are consistently better than the local model. In addition, the accuracy decreases sharply as the sentence length increases, with the local model suffering more severely from larger sentences.

To understand the effectiveness of the proposed syntactic features, we examine the relation F-scores with respect to entity distances. Miwa and Bansal (2016) exploit the shortest dependency path, which can make the distance between two entities closer compared with their sequential distance, thus facilitating relation extraction. We verify whether the proposed syntactic features can benefit our model similarly. As shown in Figure 7, the F-scores of entity-pairs with large distances see apparent improvements, demonstrating that our use of syntactic features has a similar effect compared to the shortest dependency path.

4 Related Work

Entity recognition (Florian et al., 2004, 2006; Ratinov and Roth, 2009; Florian et al., 2010; Kuru et al., 2016) and relation extraction (Zhao and Grishman, 2005; Jiang and Zhai, 2007; Zhou et al., 2007; Qian and Zhou, 2010; Chan and Roth, 2010; Sun et al., 2011; Plank and Moschitti, 2013; Verga et al., 2016) have received much attention in the NLP community. The dominant methods treat the two tasks separately, where relation extraction is performed assuming that entity boundaries have been given (Zelenko et al., 2003; Miwa et al., 2009; Chan and Roth, 2011; Lin et al., 2016).

Several studies find that extracting entities and relations jointly can benefit both tasks. Early work conducts joint inference for separate models (Ji and Grishman, 2005; Roth and Yih, 2004, 2007). Recent work shows that joint learning and decoding with a single model brings more benefits for the two tasks (Li and Ji, 2014; Miwa and Sasaki, 2014; Miwa and Bansal, 2016; Gupta et al., 2016), and we follow this line of work in the study.

LSTM features have been extensively exploited for NLP tasks, including tagging (Huang et al., 2015; Lample et al., 2016), parsing (Kiperwasser and Goldberg, 2016; Dozat and Manning, 2016), relation classification (Xu et al., 2015; Vu et al., 2016; Miwa and Bansal, 2016) and sentiment analysis (Li et al., 2015; Teng et al., 2016). Based on the output of LSTM structures, Wang and Chang (2016) introduce segment features, and apply it to dependency parsing. The same method is applied to constituent parsing by Cross and Huang (2016). We exploit this segmental representation for relation extraction.

Global optimization and normalization has been successfully applied on many NLP tasks that involve structural prediction (Lafferty et al., 2001; Collins, 2002; McDonald et al., 2010; Zhang and Clark, 2011), using traditional discrete features. For neural models, it has recently received increasing interests (Zhou et al., 2015; Andor et al., 2016; Xu, 2016; Wiseman and Rush, 2016), and improved performances can be achieved with global optimization accompanied by beam search. Our work is in line with these efforts. To our knowledge, we are the first to apply globally optimized neural models for end-to-end relation extraction, achieving the best results on standard benchmarks.

5 Conclusion

We investigated a globally normalized end-to-end relation extraction model using neural network, based on the table-filling framework proposed by Miwa and Sasaki (2014). Feature representations are learned from several LSTM structures over the inputs, and a novel simple method is used to integrate syntactic information. Experiments show the effectiveness of both global normalization and syntactic features. Our final model achieved the best performances on two benchmark datasets.

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