

End-to-end Learning of Semantic Role Labeling Using Recurrent Neural Networks

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Abstract

Semantic role labeling (SRL) is one of the basic natural language processing (NLP) problems. To this date, most of the successful SRL systems were built on top of some form of parsing results (Koomen et al., 2005; Palmer et al., 2010; Pradhan et al., 2013), where pre-defined feature templates over the syntactic structure are used. The attempts of building an end-to-end SRL learning system without using parsing were less successful (Collobert et al., 2011). In this work, we propose to use deep bi-directional recurrent network as an end-to-end system for SRL. We take only original text information as input feature, without using any syntactic knowledge. The proposed algorithm for semantic role labeling was mainly evaluated on CoNLL-2005 shared task and achieved F_1 score of 81.07. This result outperforms the previous state-of-the-art system from the combination of different parsing trees or models. We also obtained the same conclusion with $F_1 = 81.27$ on CoNLL-2012 shared task. As a result of simplicity, our model is also computationally efficient that the parsing speed is 6.7k tokens per second. Our analysis shows that our model is better at handling longer sentences than traditional models. And the latent variables of our model implicitly capture the syntactic structure of a sentence.

1 Introduction

Semantic role labeling (SRL) is a form of shallow semantic parsing whose goal is to discover the predicate-argument structure of each predicate in a given input sentence. Given a sentence, for each target verb (predicate) all the constituents in

the sentence which fill a semantic role of the verb have to be recognized. Typical semantic arguments include Agent, Patient, Instrument, etc., and also adjuncts such as Locative, Temporal, Manner, Cause, etc.. SRL is useful as an intermediate step in a wide range of natural language processing (NLP) tasks, such as information extraction (Bastianelli et al., 2013), automatic document categorization (Persson et al., 2009) and question-answering (Dan and Lapata, 2007; Surdeanu et al., 2003; Moschitti et al., 2003).

SRL is considered as a supervised machine learning problem. In traditional methods, linear classifier such as SVM is often employed to perform this task based on features extracted from the training corpus. Actually, people often treat this problem as a multi-step classification task. First, whether an argument is related to the predicate is determined; next the detail relation type was decided (Palmer et al., 2010).

Syntactic information is considered to play an essential role in solving this problem (Punyakanok et al., 2008a). The location of an argument on syntactic tree provides an intermediate tag for improving the performance. However, building this syntactic tree also introduces the prediction risk inevitably. The analysis in (Pradhan et al., 2005) found that the major source of the incorrect predictions was the syntactic parser. Combination of different syntactic parsers was proposed to address this problem, from both feature level and model level (Surdeanu et al., 2007; Koomen et al., 2005; Pradhan et al., 2005).

Besides, feature templates in this classification task strongly rely on the expert experience. They need iterative modification after analyzing how the system performs on development data. When the corpus and data distribution are changed, or when people move to another language, the feature templates have to be re-designed.

To address the above issues, (Collobert et al.,

2011) proposed a unified neural network architecture using word embedding and convolution. They applied their architecture on four standard NLP tasks: Part-Of-Speech tagging (POS), chunking (CHUNK), Named Entity Recognition (NER) and Semantic Role Labeling (SRL). They were able to reach the previous state-of-the-art performance on all these tasks except for SRL. They had to resort to parsing features in order to make the system competitive with state-of-the-art performance.

In this work, we propose an end-to-end system using deep bi-directional long short-term memory (DB-LSTM) model to address the above difficulties. We take only original text as the input features, without any intermediate tag such as syntactic information. The input features are processed by the following 8 layers of LSTM bi-directionally. At the top locates the conditional random field (CRF) model for tag sequence prediction. We achieve the state-of-the-art performance of f-score $F_1 = 81.07$ on CoNLL-2005 shared task and $F_1 = 81.27$ on CoNLL-2012 shared task. At last, we find the traditional syntactic information can also be inferred from the learned representations.

2 Related Work

People solve SRL problems in two major ways. The first one follows the traditional spirit widely used in NLP basic problems. A linear classifier is employed with feature templates. Most efforts focus on how to extract the feature templates that can best describe the text properties from training corpus. One of the most important features is from syntactic parsing, although syntactic parsing is also considered as a difficult problem. Thus system combination appear to be the general solution.

In the work of (Pradhan et al., 2005), the syntactic tags are produced by Charniak parser (Charniak, 2000; Charniak and Johnson, 2005) and Collins parser (Collins, 2003) respectively. Based on this, different systems are built to generate SRL tags. These SRL tags are used to extend the original feature templates, along with flat syntactic chunking results. At last another classifier learns the final SRL tag from the above results. In their analysis, the combination of three different syntactic view brings large improvement for the system.

Similarly, Koomen et al. (Koomen et al., 2005) combined the system in another way. They built

multiple classifiers and then all outputs are combined through an optimization problem. Surdeanu et al. fully discussed the combination strategy in (Surdeanu et al., 2007).

Beyond the above traditional methods, the second way try to solve this problem without feature engineering. Collobert et al. (Collobert et al., 2011) introduced a neural network model consists of word embedding layer, convolution layers and CRF layer. This pipeline addressed the data sparsity by initializing the model with word embeddings which is trained from large unlabeled text corpus. However, the convolution layer is not the best way to model long distance dependency since it only includes words within limited context. So they processed the whole sequence for each given pair of argument and predicate. This results in the computational complexity of $O(n_p L^2)$, with L denoting the sequence length and n_p the number of predicate, while the complexity of our model is linear ($O(n_p L)$). Moreover, in order to catch up with the performance of traditional methods, they had to incorporate the syntactic features by using parse trees of Charniak parser (Charniak, 2000) which still provides the major contribution.

At the inference stage, structural constraints often lead to improved results (Punyakanok et al., 2008b). The constraints comes from annotation conventions of the task and other linguistic considerations. With dynamic programming, (Täckström et al., 2015) enhance the inference efficiency further. But designation of the constraints depends much on the linguistic knowledge.

Nevertheless, the attempts of building end-to-end systems for NLP become popular in recent years. Inspired by the work in computer vision, people hierarchically organized a window of words through convolution layers in deep form to account for the higher level of organization to solve the document classification task (Kim, 2014; Zhang and LeCun, 2015). Step further, people have also achieved success in directly mapping the sequence to sequence level target as the work in dependency parsing and machine translation (Vinyals et al., 2014; Sutskever et al., 2014).

3 Approaches

In this paper, we propose an end-to-end system based on recurrent topology. Recurrent neural network (RNN) has natural advantage in modeling sequence problems. The past information is built

up through the recurrent layer when model consumes the sequence word by word as shown in E-q. 1. x and y are the input and output of the recurrent layer with (t) denoting the time step, w_f^m and w_i^m are the matrix from input or recurrent layer to hidden layer. σ is the activation function. Without $y^{(t-1)}$ term, the rnn model returns to the feed forward form.

$$y_m^{(t)} = \sigma\left(\sum_f w_f^m x_f^{(t)} + \sum_i w_i^m y_i^{(t-1)}\right) \quad (1)$$

However, people often met with two difficulties. First, information of the current word strongly depends on distant words, rather than its neighborhood. Second, gradient parameters may explode or vanish especially in processing long sequences (Bengio et al., 1994). Thus long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997) was proposed to address the above difficulties.

In the following part, we will first give a brief introduction about the LSTM and then demonstrate how to build up a network based on LSTM to solve a typical sequence tagging problem: semantic role labeling.

3.1 Long Short-Term Memory (LSTM)

Long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997; Graves et al., 2009) is an RNN architecture specifically designed to address the vanishing gradient and exploding gradient problems. The hidden neural units are replaced by a number of memory blocks. Each memory block contains several cells, whose activations are controlled by three multiplicative gates: the input gate, forget gate and output gate. With the above change, the original rnn model is improved to be:

$$y_m^{(t)} = \sigma(s_{c,m}^{(t)}) \cdot \pi_m^{(t)} \quad (2)$$

$$= \sigma(n_m^{(t)} \rho_m^{(t)} + \phi_m^{(t)} s_{c,m}^{(t-1)}) \cdot \pi_m^{(t)} \quad (3)$$

Now y is the memory block output. n is equivalent to the original hidden value y in rnn model. ρ , ϕ and π are the input, forget and output gates value. $s_{c,m}$ is state value of cell c in block m and c is fixed to be 1 and omitted in common work. The computation of three multiplicative gates comes from input value, recurrent value and cell state value with different activations σ respectively as shown in the

following and Fig. 1:

$$n_m^{(t)} : \sigma_n\left(\sum_f w_{f,n}^m x_f^{(t)} + \sum_i w_{i,n}^m y_i^{(t-1)}\right) \quad (4)$$

$$\rho_m^{(t)} : \sigma_\rho\left(\sum_f w_{f,\rho}^m x_f^{(t)} + \sum_i w_{i,\rho}^m y_i^{(t-1)} + w_\rho^m s_m^{(t-1)}\right)$$

$$\phi_m^{(t)} : \sigma_\phi\left(\sum_f w_{f,\phi}^m x_f^{(t)} + \sum_i w_{i,\phi}^m y_i^{(t-1)} + w_\phi^m s_m^{(t-1)}\right)$$

$$\pi_m^{(t)} : \sigma_\pi\left(\sum_f w_{f,\pi}^m x_f^{(t)} + \sum_i w_{i,\pi}^m y_i^{(t-1)} + w_\pi^m s_m^{(t-1)}\right)$$

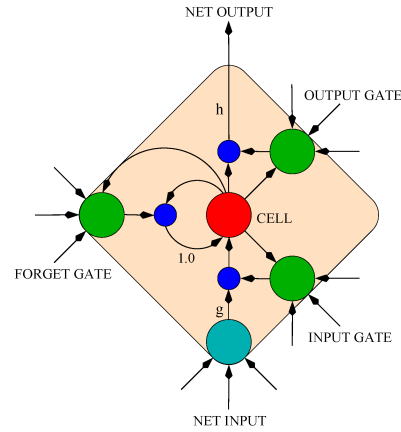


Figure 1: LSTM memory block with a single cell. (Graves et al., 2009)

The effect of the gates is to allow the cells to store and access information over long periods of time. When the input gate is closed, the new coming input information will not affect the previous cell state. Forget gate is used to remove the historical information stored in the cells. The rest of the network can access the stored value of a cell only when its output gate is open.

In language related problems, the structural knowledge can be extracted out by processing sequences both forward and backward so that the complementary information from the past and the future can be integrated for inference. Thus bi-directional LSTM (B-LSTM) containing two hidden layers were proposed (Schuster and Paliwal, 1997). Both hidden layers connect to the same input layer and output layer, processing the same sequence in two directions respectively (A. Graves, 2013).

In this work, we utilize the bi-directional information in another way. First a standard LSTM processes the sequence in forward direction. The output of this LSTM layer is taken by the next

LSTM layer as input, processed in reversed direction. These two standard LSTM layers compose a pair of LSTM. Then we stack LSTM layers pair after pair to obtain the deep LSTM model. We call this topology as deep bi-directional LSTM (DB-LSTM) network. Our experiments show that this architecture is critical to achieve good performance.

3.2 Pipeline

We process the sequence word by word. Two input features play an essential role in this pipeline: predicate (pred) and argument (argu), with argument describing the word under processing. The output for this pair of words is their semantic role. If a sequence has n_p predicates, we will process this sequence n_p times.

We also introduce two other features, predicate context (ctx-p) and region mark (m_r). Since a single predicate word can not exactly describe the predicate information, especially when the same words appear more than one times in a sentence. With the expanded context, the ambiguity can be largely eliminated. Similarly, we use region mark $m_r = 1$ to denote the argument position if it locates in the predicate context region, or $m_r = 0$ if not. These four simple features are all we need for our SRL system. In Tab. 1 we give an example sequence with the labels for each word. We do not use other types of features such as part of speech (POS), syntactic parsing, etc..

time	argu	pred	ctx-p	m_r	label
1	A	set	been set .	0	B-A1
2	record	set	been set .	0	I-A1
3	date	set	been set .	0	I-A1
4	has	set	been set .	0	O
5	n't	set	been set .	0	B-AM-NEG
6	been	set	been set .	1	O
7	set	set	been set .	1	B-V
8	.	set	been set .	1	O

Table 1: An example sequence with 4 input features: argument, predicate, predicate context (context length is 3), region mark. ‘‘IOB’’ tagging scheme is used (Collobert et al., 2011).

Because the large number of parameters associated with the argument words, similar to (Collobert et al., 2011), the pre-trained word representations are employed to address the data sparsity issue. We used a large unlabeled text corpus to train a neural language model (NLM) (Bengio et al., 2006; Bengio et al., 2003) and then initial-

ized the argument and predicate word representations with parameters from the NLM representations. There are various ways of obtaining good word representations (Mikolov et al., 2013; Collobert and Weston, 2008; Mnih and Kavukcuoglu, 2013; Yu et al., 2014). A systematic comparison of them on the task of SRL is beyond the scope of this work.

The above four features are concatenated to be the input representation at this time step for the following LSTM layers. As described in Sec. 3.1, we use DB-LSTM topology to learn the sequence knowledge and we build up to 8 layers of DB-LSTM in our work.

As in traditional methods, we employ CRF (Lafferty et al., 2001) on top of the network for the final prediction. It takes the representations provided by the last LSTM layer as input to model the strong dependance among adjacent tags.

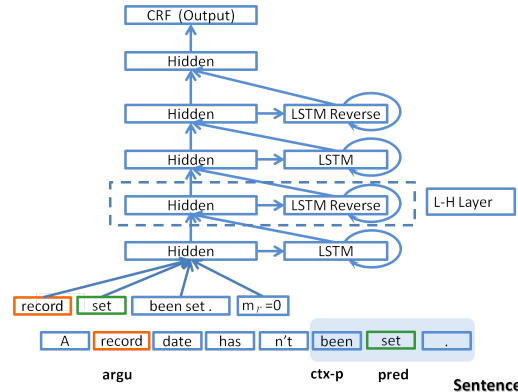


Figure 2: DB-LSTM network. Shadow part denote the predicate context within length 1.

The complete model with 4 LSTM layers is illustrated in Fig. 2. At the bottom of the graph locates the word sequence in Tab. 1. For a given time step (step 2 as an example), argument and predicate are specified with different color. We use the shadowed region to denote the predicate context. The temporal expanded version of the model is shown in Fig. 3. L-H denotes the LSTM hidden layer.

We use the stochastic gradient descent (SGD) algorithm as the training technique for the whole pipeline (Lecun et al., 1998). For a given sequence, we look up the embedding of each word and process this vector with the following LSTM layers for the high level representation. After having finished the whole sequence, we take the representations of all time steps as the input features

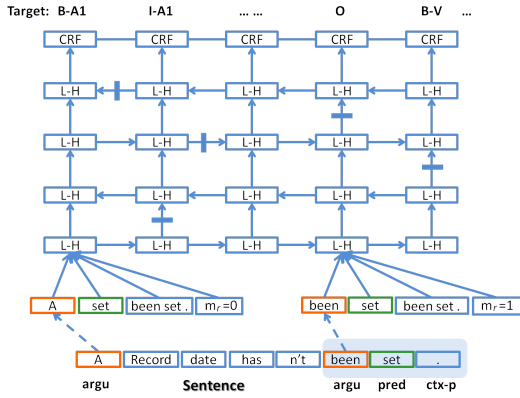


Figure 3: Temporal expanded DB-LSTM network. Bars denote that the connections are blocked by the closed gates. Shadow part denotes the predicate context.

for CRF to perform the sequence tagging task. The traditional viterbi decoding is used for inference. The gradient of the log-likelihood of the tag sequence with respect to the input of the CRF is calculated and back-propagated to all the DB-LSTM layers to get the gradient of the parameters (Collobert et al., 2011).

4 Experiments

We mainly evaluated and analyzed our system on the commonly used CoNLL-2005 shared task data set and the conclusions are also validated on CoNLL-2012 shared task.

4.1 Data set

CoNLL-2005 data set takes section 2-21 of Wall Street Journal (WSJ) data as training set, and section 24 as development set. The test set consists of section 23 of WSJ concatenated with 3 sections from Brown corpus (Carreras and Màrquez, 2005). CoNLL-2012 data set is extracted from OntoNotes v5.0 corpus. The description and separation of train, development and test data set can be found in (Pradhan et al., 2013).

4.2 Word embedding

We trained word embeddings with English Wikipedia (Ewk) corpus using NLM (Bengio et al., 2006). The corpus contains 995 million tokens. We transformed all the words into their lowercase and the vocabulary size is 4.9 million. About 5% words in CoNLL 2005 data set can not be found in Ewk dictionary and are marked as

<unk>. In all experiments, we use the same word embedding with dimension 32.

4.3 Network topology

In this part, we will analyze the performance of two different networks, the CNN and LSTM network. Although at last we find CNN can not provide the results as good as that from LSTM, the analysis still help us to gain a deep insight of this problem. In CNN, we add argument context as the fifth feature and the other four features are the same as that used in LSTM. In order to have good understanding of the contribution from each modeling decision, we started from a simple model and add more units step by step.

4.3.1 Convolutional neural network

Using CNN to solve SRL problem has been introduced in (Collobert et al., 2011). Since we only focus on the analysis of features, a simplified version is used here.

Our feature set consists of five parts as described above. The representation of argument and predicate can be obtained by looking up the Emb(Ewk) dictionary. And the representation of argument context and predicate context can be obtained by concatenating the embedding of each word in the context. For each of the above four parts, we add a hidden layer. Then all these four hidden layers together with region mark are projected onto the next hidden layer. At last we use a CRF layer for prediction (See Fig. 4). With above set up, the computational complexity is $O(n_p L)$.

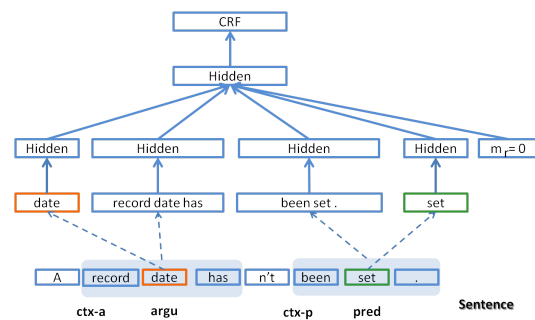


Figure 4: CNN Pipeline. Shadow parts denote the argument context and predicate context respectively

The size of hidden layers connected to argument or predicate is set to be $h_{1w} = 32$. The size of the other two hidden layers connected to context embedding is set to be $h_{1c} = 128$ since the

corresponding inputs are larger. To simplify the parameter setting and results comparison, we use the same learning rate $l = 1 \times 10^{-3}$ for each layer and keep this rate a constant during model training. The second hidden layer dimension h_2 is also 128. All hidden layer activation function is \tanh .

In Tab. 2, it is shown that longer argument and predicate context result in better performance, since longer context brings more information. We observe the same trends in other NLP experiments, such as NER, POS tagging. The difference is that we do not need to use the context length up to 11. This is because most of the useful information for NER and POS tagging is local respect the label position, while in SRL there exists long distance relationship. So in traditional methods for SRL, syntactic trees are often introduced to account for such relation. In order to see whether the improvement from CNN-2 to CNN-3 is due to longer context or larger model size, we tested a model CNN-6 with same context length but more model parameters. As we can see from the result of CoNLL-2005 data set (Tab. 2), larger model does not improve the result.

name	h_{1c}	ctx-a	ctx-p	m_r	$F_1(\text{dev})$	F_1
CNN-1	128	1	5	y	41.22	41.24
CNN-2	128	5	5	y	51.83	52.09
CNN-3	128	11	5	y	52.81	53.07
CNN-4	128	11	1	y	49.69	50.70
CNN-5	128	11	5	n	36.40	37.50
CNN-6	256	5	5	y	51.60	51.91

Table 2: F_1 of CNN method on development set and test set of CoNLL-2005 data set.

Without using region mark (m_r) feature, the F_1 drops from the 53.07 of CNN-3 to the 37.50 of CNN-5. Since it is generally believed that words near the predicate are more likely to be related to the predicate.

SRL is a typical problem with long distance dependency, while the convolution operation can only learn the knowledge from the limited neighborhood. This is why we have to introduce long context. However, the language information can not be expressed just by linearly expanding the context as what we did in CNN pipeline. In order to better summarize the sequence structure, we turn to LSTM network.

4.3.2 LSTM network

Here the feature set consists of four parts. Argument and predicate are necessary parts in this

problem. In recurrent model, argument context (ctx-a) is no longer needed and we only expand the predicate context. We also need the region mark defined in the same way as in CNN. The architecture has been shown in Fig. 2 and described in Sec. 3.2.

Since it is difficult to propagate the error from the top to the bottom layers, we use two learning rates. At the bottom, *i.e.* from embeddings to the first LSTM layer, we use $l_b = 1 \times 10^{-2}$ for model depth $d \leq 4$ and $l_b = 2 \times 10^{-2}$ for $d > 4$. For the other LSTM layers and CRF layer, we set learning rate $l = l_b \times 10^{-3}$. We kept all learning rates constant during training. The model size can be enlarged by increasing the number of LSTM layers (d) or the dimension of hidden layers (h). L2 weight decay in SGD is used for model regularization and we set its strength $r_2 = 8 \times 10^{-4}$:

$$w \leftarrow w - l \cdot (g + r_2 \cdot w) \quad (5)$$

where w denotes the parameter, g the gradient of the log likelihood of the label with respect to the parameter.

We started on CoNLL-2005 dataset from a small model with only one LSTM layer and $h = 32$. All word embeddings were randomly initialized. Predicate context length was 1. Region mark is not used. With this model, we obtained $F_1 = 49.44$ (Tab. 3), better than that of CNN without using argument context (41.24) or region mark (37.50). This result suggests that, the recurrent structure can extract sequential information more effectively than CNN.

By adding predicate context with length 5, F_1 is improved from 49.44 to 56.85 (Tab. 3). This is because we only recurrently process the argument word, so we still need predicate context for more detail. Further more, F_1 rises to 58.71 with region mark feature. The reason is the same as we explained in CNN pipeline.

Next we change the random initialization of word representation to the pre-trained word representation from Emb(Ewk). This representation is fixed in the training process. F_1 rises to 65.11 (See Tab. 3).

So far, we have shown the effect from each part of features in LSTM network. The conclusion is consistent with what we found in CNN network. Besides, LSTM exhibits better abilities to learn the sequence structure. Next, we gradually increase the model size to further enhance the performance.

Emb	d	ctx-p	m_r	h	F_1 (dev)	F_1
CoNLL-2005 data set						
Ran	1	1	n	32	47.88	49.44
Ran	1	5	n	32	54.63	56.85
Ran	1	5	y	32	57.13	58.71
Ewk	1	5	y	32	64.48	65.11
Ewk	2	5	y	32	72.72	72.56
Ewk	4	5	y	32	75.08	75.74
Ewk	6	5	y	32	76.94	78.02
Ewk	8	5	y	32	77.50	78.28
Ewk	8	5	y	64	77.69	79.46
Ewk	8	5	y	128	79.10	80.28
fine tuning						
Ewk	8	5	y	128	79.55	81.07
CoNLL-2012 data set						
Ewk	8	5	y	128	80.51	80.70
fine tuning						
Ewk	8	5	y	128	81.07	81.27

Table 3: F_1 with LSTM method on development set and test set of CoNLL-2005 data set and CoNLL-2012 data set. Emb: the type of embedding. d: the number of LSTM layers. ctx-p: predicate context length. m_r : region mark feature. h: hidden layer size.

We find that the critical improvement comes from increasing the depth of LSTM network. After adding a reversed LSTM layer, F_1 is improved from 65.11 to 72.56. And the F_1 of the system with $d = 4, 6, 8$ are 75.74, 78.02 and 78.28 respectively. With 6-layer network, we have outperformed the CoNLL-2005 shared task winner system with $F_1 = 77.92$ (Koomen et al., 2005). Our experiment results also show that the further performance gain by increasing the depth from 6 to 8 is relative small.

Another way to increase the model size is to increase the hidden layer dimension h . We gradually increase the dimension from 32 to 64, 128, and the corresponding results are listed in Tab. 3. The best F_1 we obtained is 80.28 with $h = 128$. We also show the result $F_1 = 80.70$ on CoNLL-2012 dataset in Tab. 3 with exactly the same setup.

In the above experiments, learning rate and weight decay rate are fixed for the sake of simplicity in comparing different models. To further improve the model, we perform a fine tuning step to adjust the parameters based on previously trained model. This includes the relaxation of weight decay and decrease of learning rate. We set $r_2 = 4 \times 10^{-4}$ and $l_b = 1 \times 10^{-2}$, and obtain $F_1 = 81.07$ as the final result of CoNLL-2005 data set and $F_1 = 81.27$ of CoNLL-2012 data set.

	F_1	F_1		
	dev	test	WSJ	Brown
CoNLL-2005				
Koomen	77.35	77.92	79.44	67.75
Koomen (single parser)	74.76	-	-	-
Pradhan	78.34	77.30	78.63	68.44
Collobert (w/ parser)	75.42	76.06	-	-
Collobert (w/o parser)	72.29	74.15	-	-
Surdeanu	-	-	80.6	70.1
Toutanova	78.6	-	80.3	68.8
Täckström	78.6	-	79.9	71.3
Ours	79.55	81.07	82.84	69.41
	F_1	F_1		
CoNLL-2012	dev	test	-	-
Pradhan	-	75.53		
Täckström	79.1	79.4		
Ours	81.07	81.27		

Table 4: Comparison with previous methods.

In Tab. 4, we compare the performance of other works. On CoNLL-2005 shared task, merging syntactic tree at feature level instead of model level exhibits the similar performance with $F_1 = 77.30$ (Pradhan et al., 2005). After further investigation on model combination, Surdeanu et al. obtained a better system (Surdeanu et al., 2007). We also list the results from (Toutanova et al., 2008) and (Täckström et al., 2015) of the joint model with additional considerations of standard linguistic assumptions. For convolution based methods (Collobert et al., 2011), the best F_1 is 76.06, in which syntactic parser plays an essential role. The result without using parser drops down to 74.15. On Brown set, we observe the better performance from the work of (Surdeanu et al., 2007) and (Täckström et al., 2015). We hypothesize that DB-LSTM is a data-driven method that can not performs well on out-domain dataset.

On CoNLL-2012 data set, the traditional method gives $F_1 = 75.53$ (Pradhan et al., 2013) and a dynamic programming algorithm for efficient constrained inference in SRL gives $F_1 = 79.4$ (Täckström et al., 2015), both of them also rely on syntax trees.

Since the input feature size is much smaller than the traditional sparse feature templates, the inference stage is very efficient that the model can process 6.7k tokens per second on average.

4.4 Analysis

We analyze our results on CoNLL-2005 data set. First we list the details including the performance on each sub-classes in Tab. 5. The results of CoNLL-2005 shared task winner system (Koomen et al., 2005) are also shown for comparison. Their

Data set	Results (Koomen <i>et.al.</i>)			Results (Ours)		
	P	R	F_1	P	R	F_1
dev	80.05	74.83	77.35	79.69	79.41	79.55
dev (s)	75.40	74.13	74.76	79.69	79.41	79.55
test WSJ	82.28	76.78	79.44	82.92	82.75	82.84
test Brown	73.38	62.93	67.75	70.70	68.17	69.41
test	81.18	74.92	77.92	81.33	80.80	81.07
A0	88.22	87.88	88.05	90.08	89.73	89.91
A1	82.25	77.69	79.91	82.00	82.87	82.43
A2	78.27	60.36	68.16	70.50	72.63	71.55
A3	82.73	52.60	64.31	63.98	55.68	59.54
AM-ADV	63.82	56.13	59.73	66.03	53.00	58.80
AM-DIS	75.44	80.62	77.95	73.76	78.07	75.85
AM-LOC	66.67	55.10	60.33	65.17	58.48	61.65
AM-MNR	66.79	53.20	59.22	56.36	54.63	55.48
AM-MOD	96.11	98.73	97.40	94.62	98.60	96.57
AM-NEG	97.40	97.83	97.61	95.70	95.36	95.53
AM-TMP	78.16	76.72	77.44	78.61	82.74	80.62
R-A0	89.72	85.71	87.67	94.72	93.57	94.14
R-A1	70.00	76.28	73.01	80.00	90.40	84.88
V	98.92	97.10	98.00	98.63	98.63	98.63

Table 5: F_1 on each sub sets and classes (CoNLL-2005). (We remove the classes with low statistics.)

final system is the combination of the results of 5 parsing trees from two different parsers. They also reported the scores of each single system on development set and we list the best one of them (dev(s)).

We observe the improvement of F_1 on development set and test set are 2.20 and 3.15 respectively. For single system, the improvement is 4.79 on development set. We also notice that our model show improvement on both WSJ and Brown test set. The advantage of our model is even more significant when comparing with the previous effort of end-to-end training of SRL model (Collobert et al., 2011). Without using linguistic features from parse tree, the F_1 of Collobert’s model is 74.15, which is 6.92 lower than our model.

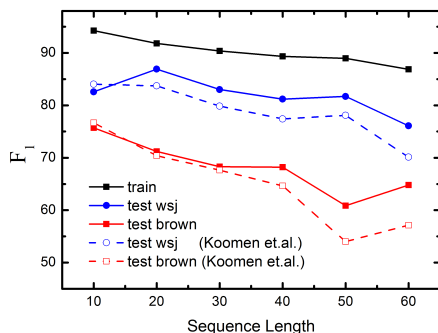


Figure 5: F_1 vs. sentence length (CoNLL-2005).

In order to analyze the performance of our model on the sentences with different lengths, we split the data into 6 bins according to the sentence length, with bin width being 10 words and the last

bin includes sequences with $L > 50$ because of insufficient data for longer sentences. Fig. 5 shows F_1 scores at different sequence lengths on WSJ test data and Brown test data for our model and Koomen’s model (baseline) (Koomen et al., 2005). In all curves, performance degrades with increased sentence length. However, the performance gain of our model over the baseline model is larger for longer sentences.

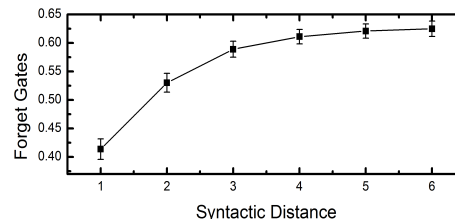


Figure 7: Averaged Forget gates value vs. Syntactic distance (CoNLL-2005). The last point includes instances with syntactic distance $d_s \geq 6$.

Since we do not use any syntactic information as input feature, we are curious about whether this information can be extracted out from the system parameters. In LSTM, forget gates are used to control the use of historical information. We compute the average value v_{fg} of forget gates of the 7th LSTM layer at word position for a given sentence. We also introduce a variable named syntactic distance d_s to represent the number of edges between argument word and predicate word in the dependency parsing tree. Four example sentences are shown in Fig. 6. For each figure, the bottom axis denotes an example sentence. At the top of each graph is the corresponding dependency tree built from gold dependency parsing tag. At the bottom, v_{fg} and d_s are shown in black and red line. Noticed that the higher forget gates values means “Remember” and smaller values “Forget”. Smaller d_s means that it is easy to make prediction that long history is unnecessary. On the contrary, large d_s results in a difficult prediction that long historical information is needed. We also computed the average v_{fg} over instances and found it monotonously increases with d_s (Fig. 7). The coincidence of v_{fg} and d_s suggests that the model implicitly captures some syntactic structure.

5 Conclusion and Future work

We investigate a traditional NLP problem SRL with DB-LSTM network. With this model, we are

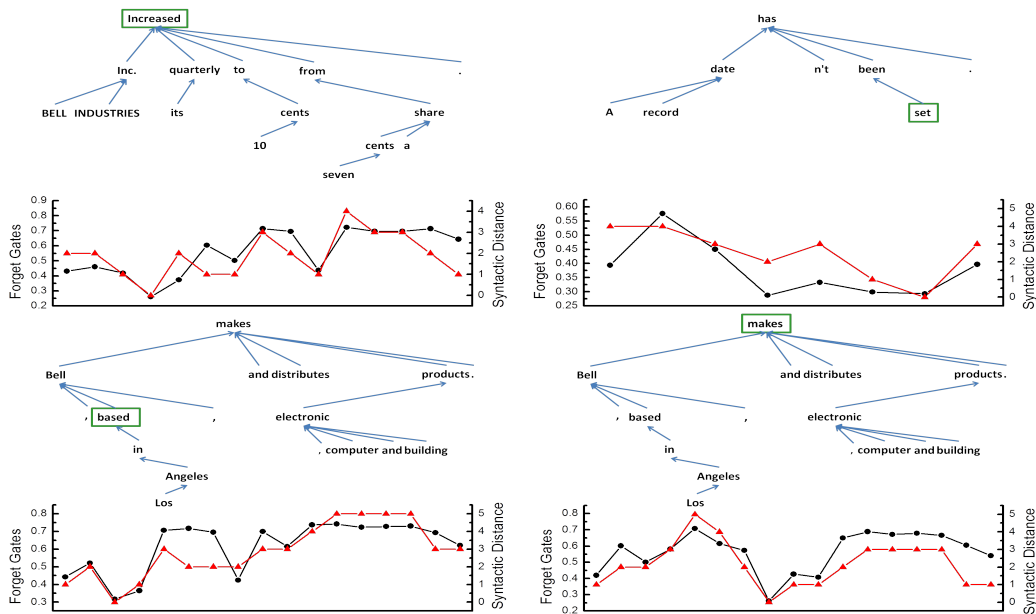


Figure 6: Forget gates value *vs.* Syntactic distance on four example sentences. Top: dependency parsing tree from gold tag. Green square word: predicate word. Bottom black solid lines: forget gates value at each time step. Bottom red empty square lines: gold syntactic distance between the current argument and predicate.

able to bypass the traditional steps for extracting the intermediate NLP features such as POS and syntactic parsing and avoid human engineering the feature templates. The model is trained to predict the SRL tag directly from the original word sequence with four simple features without any explicit linguistic knowledge. Our model achieves F_1 score of 81.07 on CoNLL-2005 shared task and 81.27 on CoNLL-2012 shared task, both outperforming the previous systems based on parsing results and feature engineering, which heavily rely on the linguistic knowledge from expert. Furthermore, the simplified feature templates results in high inference efficiency with 6.7k tokens per second.

In our experiments, increasing the model depth is the major contribution to the final improvement. With deep model, we achieve strong ability of learning semantic rules without worrying about over-fitting even on such limited training set. It also outperforms the convolution method with large context length. Moreover, with more sophisticatedly designed network and training technique based on LSTM, such as the attempt to integrate the parse tree concept into LSTM framework (Tai et al., 2015), we believe the better performance can be achieved.

We show in our analysis that for long sequences

our model has even larger advantage over the traditional models. On one hand, LSTM network is capable of capturing the long distance dependency especially in its deep form. On the other hand, the traditional feature templates are only good at describing the properties in neighborhood and a small mistake in syntactic tree will results in large deviation in SRL tagging. Moreover, from the analysis of the internal states of the deep network, we see that the model implicitly learn to capture some syntactic structure similar to the dependency parsing tree.

It is encouraging to see that deep learning models with end-to-end training can outperform traditional models on tasks which are previously believed to heavily depend on syntactic parsing (Koomen et al., 2005; Pradhan et al., 2013). However, we recognize that semantic role labeling itself is an intermediate step towards the language problems we really care about, such as question answering, information extraction etc. We believe that end-to-end training with some suitable deep structure yet to be invented might be proven to be effective to solving these problems. And we are seeing some recent active research exploring this possibility (Weston et al., 2014; Weston et al., 2015; Graves et al., 2014).

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