# Adaptive Convolution for Semantic Role Labeling

Kashif Munir, Hai Zhao, and Zuchao Li

Abstract-Semantic role labeling (SRL) aims at elaborating the meaning of a sentence by forming a predicate-argument structure. Recent researches depicted that the effective use of syntax can improve SRL performance. However, syntax is a complicated linguistic clue and is hard to be effectively applied in a downstream task like SRL. This work effectively encodes syntax using adaptive convolution which endows strong flexibility to existing convolutional networks. The existing CNNs may help in encoding a complicated structure like syntax for SRL, but it still has shortcomings. Contrary to traditional convolutional networks that use same filters for different inputs, adaptive convolution uses adaptively generated filters conditioned on syntacticallyinformed inputs. We achieve this with the integration of a filter generation network which generates the input specific filters. This helps the model to focus on important syntactic features present inside the input, thus enlarging the gap between syntax-aware and syntax-agnostic SRL systems. We further study a hashing technique to compress the size of the filter generation network for SRL in terms of trainable parameters. Experiments on CoNLL-2009 dataset confirm that the proposed model substantially outperforms most previous SRL systems for both English and Chinese languages.

Index Terms—Semantic role labeling, argument identification, argument classification, adaptive convolution, semantic parsing.

## I. INTRODUCTION

C EMANTIC role labeling (SRL), also known as shallow semantic parsing, conveys the meaning of a sentence by forming a predicate-argument structure for each predicate in a sentence, which is generally described as the answer to the question "Who did what to whom, where and when?". The relation between a specific predicate and its argument provides an extra layer of abstraction beyond syntactic dependencies (subject and object) [1], such that the labels are insensitive to syntactic alternations and can also be applied to nominal predicates. Given a sentence in Figure 1, SRL pipeline framework consists of 4 subtasks, including predicate identification (makes), predicate disambiguation (make.02), arguments identification (Someone) and arguments classification (Someone is A0 for predicate makes). SRL is a core task of natural language processing (NLP) having wide range of applications such as neural machine translation [2], information extraction [3], question answering [4], [5], emotion recognition from text [6], document summarization [7] etc.

This paper was partially supported by National Key Research and Development Program of China (No. 2017YFB0304100), Key Projects of National Natural Science Foundation of China (U1836222 and 61733011), Huawei-SJTU long term AI project, Cutting-edge Machine Reading Comprehension and Language Model (Corresponding author: Hai Zhao).

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Fig. 1. Semantic role labeling example.

Semantic role labeling can be categorized into two categories, span and dependency. Both types of SRL are useful for formal semantic representations but dependency based SRL is better for the convenience and effectiveness of semantic machine learning. Johansson and Nugues [8] concluded that the best dependency based SRL system outperforms the best span based SRL system through gold syntactic structure transformation. The same conclusion was also verified by Li *et al.* [9] through a solid empirical verification. Furthermore, since 2008, dependency based SRL has been more studied as compared to span based SRL. With this motivation, we focus on dependency based SRL, which is mainly popularized by CoNLL-2008 and CoNLL-2009 shared tasks [10], [11].

The traditional approaches to SRL focus on feature engineering which struggles in apprehending discriminative information [12], [13] while neural networks are proficient enough to extract features automatically [14], [15]. Specifically, since large scale empirical verification of Punyakanok et al. [16], syntactic information has been proven to be extremely beneficial for SRL task. Later works [17], [18], [19] achieve satisfactory performance for SRL with syntax-agnostic models which creates conflict with the long-held belief that syntax is essential for high-performance SRL [20]. The study of Li et al. [21] shows that the empirical results from neural models on the less importance of syntax indicate a potential challenge and despite the satisfactory performance of syntax-agnostic SRL systems, the reasons behind the absence of syntax in these models are three-fold. First, the effective incorporation of syntax in neural SRL models is guite challenging as compared to traditional approaches. Second, neural SRL models may cover partial syntactic clues more or less. Third, syntax has always been a complicated formalism in linguistics and its not easy to encode syntax for later usage. Recently, many works have been published for the effective incorporation of syntax in SRL systems. Qian et al. [22] propose syntax aware long short term memory (LSTM) to directly model complex syntax parsing information in an architecture engineering way to enhance SRL performance. Similarly, Marcheggiani and Titov [23] present a syntactic graph convolutional neural network (GCNN) based model for SRL to further enhance the performance. Given the experimental facts that syntax can alleviate SRL performance if incorporated effectively in the neural model, we seek to effectively model complex

dependency parsing information in a neural model.

Furthermore, neural networks involving convolution neural networks (CNNs) have shown remarkable achievements in different fields of NLP [24], [25], [26], [27], [28]. The driving force behind CNNs is the use of a convolution operation to screen the local information present in the inputs (either directly from the text or from intermediate hidden states of neural networks) by using a set of filters. Convolutional filters are like a pool of questions that ask for the intensity of particular patterns in the inputs and the convolution operation helps in retrieving the answers from the inputs to the questions. However, if the pool of questions is limited to a particular concept related to inputs, the convolution operation will be able to provide more concentrated answers related to questions. Contrarily, typical CNN architectures use the same set of filters under all circumstances [24], [26], which may stymie CNNs from leveraging the information from the intermediate hidden states and focus the concentration on disentangling uncertainty.

Motivated by this, we present an adaptive convolution for SRL which allows the network to utilize the syntax information they have in the inputs. The adaptive convolution uses the dynamically generated filters (questions) conditioned on inputs. We first encode the sentence using BiLSTM and Tree-Structured LSTM [21], [29] to model the syntactic information for SRL and then encoder output is fed into a filter generation network, a carefully designed modular network, which generates filters conditioned on syntactically-informed inputs for convolution operation [30]. The generated filters reflect the syntax information present in the inputs and allow the model to focus on important informative features encoded by BiLSTM and Tree-LSTM encoders. The filter generation network can be easily applied to existing CNN architectures. We further investigate a hashing technique that helps in the compression of the filter generating network to allow the adaptive convolution operation without a considerable increase in the number of parameters. Our major contributions are:

• A neural framework for SRL which effectively integrates the syntactic information of text.

• The integration of adaptive convolution in SRL model which helps the model to focus on important informative features encoded by LSTM and Tree-LSTM, and at the same time gives stronger flexibility to existing CNNs.

• The detailed study of a hashing technique to apply adaptive convolution without a considerable increase in the number of trainable parameters.

• The proposed model outperforms most previous SRL approaches on CoNLL-2009 English and Chinese datasets.

## II. RELATED WORK

Semantic role labeling was pioneered by Gildea and Jurafsky [1]. In early days of SRL research, a substantial attention has been paid to featured engineering [12], [31], [32], [33], [13], [34], [35], [36]. Pradhan *et al.* [12] deploy the SVM classifier and combine features from different syntactic parses, while Zhao *et al.* [13] use sets of language-specific features for SRL task. Li *et al.* [34] integrate features driven from verbal SRL architecture. Björkelund *et al.* [35] propose a beam search in the first stage of their system to label arguments, reranker in the second stage and then combine these scores in the third stage to label arguments for each predicate.

Yang and Zong [37] learn generalized feature vectors for arguments with a strong intuition that arguments occurring in the same syntactic positions bear the same syntactic roles. Che *et al.* [38] use a hybrid convolution tree kernel to learn link feature between argument and predicate and syntactic structure features to perform SRL task. Li and Zhou [39] present a unified framework for SRL for verbal and nominal predicates. Yang *et al.* [40] use Bi-directional Projection (BDP) method to perform bilingual semantic role labeling.

With the recent success of neural networks [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], a number of neural network based SRL systems have been proposed [51], [52], [53], [54], [55]. Foland and Martin [56] use a convolutional and time-domain neural network to develop a semantic role labeler. FitzGerald *et al.* [57] present a neural network to jointly embed arguments and their semantic roles, akin to the work [58] which presents a tensor based approach to induce compact feature representation of the words and their corresponding relations.

Recently, many researchers proposed syntax agnostic models for SRL [17], [18], [59], [60], [9] and achieve favorable results without using syntax. Cai *et al* [60] use a biaffine attention model to propose a full end-to-end syntax agnostic model for SRL. While researchers have been able to produce satisfactory results without syntax, many efforts have been made to effectively integrate syntax in SRL systems. Roth and Lapata [61] modeled the syntactic information through dependency path embeddings to achieve notable success. Marcheggiani and Titov [23] deployed a graph convolutional neural network, while Qian *et al.* [22] used SA-LSTM to encode syntactic information in sentences. Li *et al* [21] presented various ways of deploying syntactic information and concluded that the effective integration of syntax can boost SRL performance.

In this work, we follow Li *et al* [21] to integrate syntax information by using a modified version of Tree LSTM. Owing to the recent success of CNNs in NLP [24], [62], [25], we integrate adaptive convolution via a filter generation network in our SRL model. The ability of the filter generation network to produce filters conditioned on inputs allows the model to extract important syntactic features encoded by BiLSTM and Tree-LSTM encoder. We further study the effect of a hashing technique on the compression of a filter generation network in terms of trainable parameters.

#### III. METHODOLOGY

Figure 2 shows the complete architecture for SRL. Since predicates are already identified in CoNLL-2009 shared task, we focus on the identification and labeling of arguments which can be defined as a sequence tagging problem. Our SRL consists of two main modules: 1) Sentence encoder. 2) Filter generation network. In section III-A, we explain the encoder, in section III-B, how to generate filters with a filter generation network and in section III-C, how to use generated filters for adaptive convolution.



Fig. 2. Proposed SRL framework.

### A. Sentence Encoder

**Word representation:** Following the previous convention [23], we consider predicate-specific word representations for a given sentence and a known predicate. Each word representation  $x_i$  is formed by a concatenation of several features: 1) a randomly initialized embedding  $x_i^r$ . 2) a randomly initialized lemma embedding  $x_i^l$ . 3) a pre-trained embedding  $x_i^p$ . 4) a POS tag embedding  $x_i^{POS}$ . 5) a predicate related information feature  $x_i^f$  which is typically a flag {1,0} indicating if a particular word is a predicate or not. 6) Embedding from language model ELMO [63]. The final word representation will be:  $x_i = [x_i^r, x_i^l, x_i^p, x_i^{POS}, x_i^f, ELMo_i]$ .

**BiLSTM encoder:** Given an input sequence  $x = (x_1, x_2, ..., x_m)$  where *m* is the length of a sequence, we apply bidirectional long short term memory (BiLSTM) [64] to encode a sequential input. At each time step *t*, we concatenate two hidden states from BiLSTM to get  $v_t$ .

$$\overleftarrow{v_t} = \overleftarrow{LSTM}(x_t, \overleftarrow{v_{t-1}}), \quad \overrightarrow{v_t} = \overrightarrow{LSTM}(x_t, \overrightarrow{v_{t+1}})$$
$$v_t = [\overleftarrow{v_t}; \overrightarrow{v_t}] \tag{1}$$

The resulting  $v_t$  becomes an input to the next BiLSTM layer. We stack four layers of BiLSTM. **Syntactic encoder:** For effective integration of syntax in the model, we follow Li *et al.* [21] and integrate Tree LSTM in our model. Tree LSTM is an extended version of standard LSTM and focuses on modeling tree-structured topologies. This Tree LSTM is an adaption from original Child-Sum Tree LSTM, in which a single forget gate is assigned to each child unit. It takes arbitrarily many child units into account and utilizes them to compose input vectors and hidden states at each time step. For a given syntactic tree, if  $n_k$  denotes a current node, C(k) a set of its children and L(k, .) a set of dependency relations between  $n_k$  and those nodes having a connection with  $n_k$ , the Tree LSTM formulation is as follows:

$$r_{g}^{k,j} = \sigma(W^{(r)}v_{k} + U^{(r)}h_{j} + b^{L(k,j)}),$$
$$\tilde{h}_{k} = \sum_{j \in C(k)} r_{g}^{k,j} \odot h_{j}$$
(2)

$$\begin{split} i_g &= \sigma(W^{(i)}v_k + U^{(i)}\tilde{h}_k + b^{(i)}), \\ f_g^{(k,j)} &= \sigma(W^{(f)}v_k + U^{(f)}h_j + b^{(f)}), \\ o_g &= \sigma(W^{(o)}v_k + U^{(o)}\tilde{h}_k + b^{(o)}), \\ u &= \tanh(W^{(u)}v_k + U^{(u)}\tilde{h}_k + b^{(u)}), \end{split}$$

$$c_{k} = i_{g} \odot u + \sum_{j \in C(k)} f_{g}^{(k,j)} \odot c_{j},$$
  
$$h_{k} = o_{g} \odot \tanh(c_{k})$$
(3)

where  $h_j$  represents the hidden state of the *j*-th child node,  $c_k$  represents a memory cell for the head node *k* and  $b^{L(k,j)}$  is a bias term related to relation label. The output of Tree LSTM  $h_k$  is fed into a filter generation network.

#### B. Filter generation network

The filter generation network takes the output of syntactic encoder  $H = [h_1, h_2, ..., h_m]$  as the input, where  $h_k \in \mathbb{R}^d$ is a vector of dimension d at the  $k^{th}$  position in the input. The first convolution block takes syntactic encoder's output as input and produces an output with a dimension equal to the number of filters used in that particular convolution block, which becomes an input to the next convolution block and so on. The output of the filter generation network is n number of convolution filters  $\mathcal{F} = [f_1, f_2, ..., f_n]$  for each  $h_k$ , where  $f_i \in \mathbb{R}^{s,d}$  and s being the filter size.

The filter generation network produces filters in two steps: context vector generation and filter generation. The context vectors are generated with the help of a self-attention mechanism and then the filters are generated adaptively from these context vectors.

**Context vectors generation:** Before generating filters, each  $h_k$  is self-attended using a special case of self-attention [65].

$$C = a_j \cdot h_j \quad s.t \quad j \in (1,m),$$
  
$$a_j = \frac{\exp q^\top h_j}{\sum_{k=1}^m \exp(q^\top h_k)}$$
(4)

where q represents a query vector and is trainable. C contains a context vector  $c_k$  for each  $h_k$  and now trainable filters can be generated for each context vector.

**Filter generation:** Once we obtain context vectors by attending the hidden states of syntactic encoder, the filters  $\mathcal{F}$  are generated by a function of C:

$$\mathcal{F} = \mathbf{f}(C) \tag{5}$$

To train the existing CNNs after the addition of the filter generation network in an end to end fashion we need an architecture whose gradients are differentiable and can be back-propagated. For this purpose, we first use a fully connected layer and then generate filters by using two approaches: *full generation* and *hashed generation*. All the filters in  $\mathcal{F}$  are generated in the same manner, so here we will explain the procedure for one filter  $f_i$  for one context vector  $c_k$ .

*Full generation:* A simple way is to use the output of a fully connected layer as a filter. The layer takes  $c_k$  as input and generates a filter  $f_i$  as follows:

$$f_i = W_i c_k \tag{6}$$

where  $W_i \in \mathbb{R}^{(s,d) \times g}$  is a weight matrix for the generation of the *i*-th filter. *g* is the dimension of a context vector  $c_k$ .



Fig. 3. Procedure for generating each filter  $f_i$ .  $\mathcal{H}_j$  outputs the component filter by looking up the shared pool E according to the bucket index produced by  $D_j$ .

Hashed generation: The main issue with the full generation is that the number of parameters in  $W_i$  will increase quadratically between the size of  $c_k$  and the filter size and will cause memory issue in training deep adaptive convolution with full generation method. To address this issue, we use a hashing trick [30] which requires a fraction of important parameters for training. The idea of hash generation is similar to hash embeddings [66], which computes the word embeddings with a weighted sum of component embeddings from a shared pool. Similarly to hash embeddings, we generate filter  $f_i$  by a weighted sum of *component filters* from a shared pool. The shared pool  $E \in \mathbb{R}^{(1) \times \text{s.d}}$  comprises of l number of component filters and is trainable. By using predefined hash functions, we select z component filters from the shared pool and then  $f_i$  is generated by a weighted sum of z selected component filters. We explain the generation of  $f_i$  step by step as follows:

- By using z different functions (H<sub>1</sub>, H<sub>2</sub>,.., H<sub>z</sub>), we select z component filters from a predefined shared pool E.
- 2) The selected component filters in step 1 are combined as a weighted sum:  $f_i = \sum_{j=1}^{z} p_{i,j} \mathcal{H}_j(\hat{f}_i)$ .  $(p_{i,1}, ..., p_{i,z})^\top \in \mathbb{R}^z$  are known as *importance parameters* for  $f_i$  to determine the weight of a linear combination. To ensure that importance parameters are input-specific, we control  $p_{i,j}$  as follows:

$$p_{i,j} = w_{i,j}^{\top} c_k \tag{7}$$

where  $w_{i,j} \in \mathbb{R}^{g}$  is a vector to generate  $p_{i,j}$  from a context vector.

The overall generation of a filter  $f_i$  can be denoted in vector notation as follows:

$$p_{i,j} = (p_{i,1}, .., p_{i,z})^{\top}, \ \mathcal{H} = (\mathcal{H}_1, .., \mathcal{H}_z)^{\top}, \ f_i = p_{i,j}^{\top} \mathcal{H}$$
 (8)

 $\mathcal{H}$  represents ID to component filter function for generating component filters from filter IDs  $\hat{f}_i$  and is defined as  $\mathcal{H}_j = E_{D_j(\hat{f}_i)}$ , where  $\hat{f}_i$  represents the ID of the filter.  $D_j : \{1, .., z\} \rightarrow \{1, .., l\}$  is a hash function, which takes the filter ID as an input and produces a bucket index in  $\{1, 2, .., l\}$ . The row of bucket index in E will be the component filter. The procedure is shown in Figure 3.

Based on the above description, we require the following for each filter generation:

1) A trainable shared pool matrix  $E \in \mathbb{R}^{(1) \times \text{s.d.}}$ , where each row represents a component filter.

- 2) A weight matrix  $W_{i,j} \in \mathbb{R}^{g \times z}$  to create importance parameters conditioned on inputs.
- 3) z different functions  $(\mathcal{H}_1, \mathcal{H}_2, ..., \mathcal{H}_z)$ , each uniformly assigning one of the *l* component filters to each  $f_i$ .

The number of parameters required for the generation of each filter will be z \* g because we use z number of  $p_{i,j}$ . We can achieve fairly good performance by choosing a small value of z. In this particular setting, we use 5 importance parameters. This helps in a drastic reduction in the number of trainable parameters as compared to the full generation method which requires s \* d \* g number of parameters for each filter generation. The extra parameters in hash generation come from a shared pool E but its portion is relatively small because the component filters in E are shared across all the filters and its size l can be set to a moderate value (we use l = 20).

Algorithm 1: Forward propagation of proposed SRL model.

<b>Input</b> : Sentence, predicate, POS tags, dependency
tree T.
Output: SRL label
$x \leftarrow [x^r, x^l, x^p, x^{POS}, x^f, ELMo]$
for each epoch do
$v \leftarrow \text{BiLSTM encoder}(x)$
$H \leftarrow \text{syntactic encoder}(v)$
for each $h_i$ in $H$ do
for For each convolution block in CNNs do
$c_i \leftarrow \text{context vector generation}(h_i)$
$\mathcal{F} \leftarrow \text{filter generation}(c_i)$
$O \leftarrow \operatorname{convolution}(h_i, \mathfrak{F})$
convolution to $h_i$ with $\mathcal{F}$
$O \leftarrow \max \text{ pooling}(O)$
$h_i \leftarrow O$
SRL labels $\leftarrow$ MLP(softmax(H))

### C. Adaptive convolution

The filter generation network takes an input from the previous convolution block and produces an output except for the first convolution block which takes the output of the syntactic encoder as an input. The input-related generated filters are used by the adaptive convolution to produce output. Specifically, for the *j*-th position of the input window and filter  $f_i$ , the feature  $o_{i,j}$  is computed as follows:

$$o_{i,j} = \phi(f_i^{\top} h_{j:j+s-1})$$
 (9)

where  $h_{j:j+s-1}$  is the concatenation of the inputs  $[h_j, h_{j+1}, ..., h_{j+s-1}]$  and  $\phi$  is an activation function. By concatenating features  $o_{i,j}$  for all the filters in  $\mathcal{F}$  for the *j*-th position in the window, a position feature  $o_j$  is generated and the output for the adaptive convolution will be  $O = [o_1; o_2; ...; o_{m-s+1}]$ . After applying max pooling, it will become an input to the next convolution block. Algorithm 1 explains the whole procedure.

The output of the convolution operation after max pooling will be  $\mathbb{R}^n$  for each  $c_k$ , where *n* is the number of filters. The overall output of the adaptive convolution layer will be  $\mathbb{R}^{m \times n}$ . The output of the adaptive convolution layer is fed into Multi-Layer Perceptron with highway connections followed by a softmax, resulting in an output distribution over  $\mathcal{A}$  argument labels for each token in a sentence ( $\mathbb{R}^{m \times \mathcal{A}}$ ). The MLP consists of 10 layers with *ReLU* activations. To maximize the likelihood of labels, we use categorical crossentropy as the loss function.

## D. Predicate disambiguation:

Although predicates are already identified for each sentence in CoNLL-2009 dataset, predicate disambiguation is an indispensable task aiming at the identification of a predicateargument structure in a particular context. This task is comparatively easier to perform, so we use a small portion of the proposed model for this. Given  $x_i$  as explained in section III-A, we remove Tree LSTM and convolution layer, and use the remaining model for predicate disambiguation.

#### **IV. EXPERIMENTS**

Our model<sup>1</sup> is experimented on CoNLL-2009 dataset for both English and Chinese languages. For English pre-trained embeddings, we use GloVe vectors of 200 dimension [69]. For Chinese pre-trained embeddings, we train a word2vec model (200 dimension) using Wikipedia documents [70]. All the other real vectors are randomly initialized with the Guassian distribution with a standard deviation of 0.1. The dimension of lemma embedding is 200, for POS tag embedding is 32 and for predicate identification flag embedding is 16. Additionally, the dimension for ELMo<sup>2</sup> embedding is 300. To incorporate the dependency information, we use the officially given parses in CoNLL-2009 dataset. For hash convolution, the pool size is 20 and 5 number of importance parameters. We optimize the model using Adam optimizer [71] with a learning rate of  $1e^{-3}$  and a batch size of 128. For adaptive convolution, we deploy three settings for CNNs as follows:

• CNN: We use 100 filters with a window size of 3, 100 filters with a window size of 4 and 100 filters with a window size of 5.

• DPCNN: We use 100 filters for each block of convolution, each having a window size of 3 and depth is kept to 11 for both English and Chinese datasets.

• DenseCNN: In this scenario, we deploy 75 filters for each convolution block. The inputs to DenseCNN is padded to a fixed length.

#### A. Results

We compare our proposed model with the previously published papers on dependency SRL. Noteworthily, our model performs arguments identification and classification in one shot. Table I shows the results of our proposed model for English in domain and out of domain datasets. Our model outperforms most previous approaches of SRL, including ensemble models

<sup>1</sup>The code will be released at https://github.com/kashifmunir92/ adaptiveCNN\_SRL

<sup>2</sup>For Chinese, we do not use ELMo embeddings as pre-trained ELMo is available for English only.

 TABLE I

 Results on the Conll-2009 English in domain (WSJ) dataset and English out of domain (Brown) datasets.

System	English WSJ			Eng	glish Bro	own
System	Р	R	$F_1$	Р	R	$F_1$
Local model						
Zhao et al. [32]	_	_	86.2	_	_	74.6
FitzGerald et al. [57]	_	_	86.7	_	_	75.2
Roth and Lapata [61]	88.1	85.3	86.7	76.9	73.8	75.3
Marcheggiani et al. [19]	88.7	86.8	87.7	79.4	76.2	77.7
Marcheggiani and Titov [23]	89.1	86.8	88.0	78.5	75.9	77.2
He et al. [67]	89.7	89.3	89.5	81.9	76.9	79.3
Cai et al. [60]	89.9	89.2	89.6	79.8	78.3	79.0
Li et al. [21]	90.3	89.3	89.8	80.6	79.0	79.8
Li et al. [9]	89.6	91.2	90.4	81.7	81.4	81.5
(Ours) SRL-CNN full	90.5	90.7	90.6	82.1	81.6	81.8
(Ours) SRL-CNN hash	90.1	91.0	90.5	82.0	81.5	81.7
(Ours) SRL-DPCNN full	90.2	91.3	90.7	82.9	81.5	82.2
(Ours) SRL-DPCNN hash	91.1	90.2	90.6	82.5	81.3	81.9
(Ours) SRL-DenseCNN full	91.2	90.6	90.9	83.1	82.6	82.8
(Ours) SRL-DenseCNN hash	90.6	90.8	90.7	82.8	81.1	81.9
Global model						
Björkelund et al. [68]	88.6	85.2	86.9	77.9	73.6	75.7
FitzGerald et al. [57]	_	_	87.3	_	_	75.2
Roth and Lapata [61]	90.0	85.5	87.7	78.6	73.8	76.1
Ensemble model						
FitzGerald et al. [57]	_	_	87.7	_	_	75.5
Roth and Lapata [61]	90.3	85.7	87.9	79.7	73.6	76.5
Marcheggiani and Titov [23]	90.5	87.7	89.1	80.8	77.1	78.9

 TABLE II

 Results on the CoNLL-2009 Chinese test dataset.

System	Chine	se test d	lataset
System	Р	R	$F_1$
Local model			
Marcheggiani et al. [19]	83.4	79.1	81.2
Marcheggiani and Titov [23]	84.6	80.4	82.5
He et al. [67]	84.2	81.5	82.8
Cai et al. [60]	84.7	84.0	84.3
Li et al. [21]	84.8	81.2	83.0
(Ours) SRL-CNN full	83.4	83.6	83.5
(Ours) SRL-CNN hash	83.3	83.1	83.2
(Ours) SRL-DPCNN full	84.0	83.6	83.8
(Ours) SRL-DPCNN hash	83.9	83.5	83.7
(Ours) SRL-DenseCNN full	84.7	85.1	84.9
(Ours) SRL-DenseCNN hash	84.5	84.7	84.6
Global model			
Björkelund et al. [35]	84.2	75.1	78.6
Roth and Lapata [61]	83.2	75.9	79.4

For English, SRL-DenseCNN with *full generation* technique of filter generation network gives the best results in terms of  $F_1$  score and precision, while SRL-DPCNN *full* yields the best recall. We outperform syntax-agnostic model of Li *et al.* [9] and syntax aware model of Li *et al.* [21] by a margin of 0.5% and ~1.1% respectively. The same version of the proposed model also performs best on English out of domain dataset, outperforming Li *et al.* [21] and Li *et al.* [9] by a margin of 3% and 1.3% respectively, affirming the ability of the proposed model to learn and generalize the latent semantic preferences present in the data.

Table II shows the results of our model on CoNLL-2009 Chinese test dataset. Except for the use of ELMo, we use the same parameters while training the model on Chinese dataset. The results depict that the model overwhelmingly surpasses the previous best performing models, visualizing the proposed model as robust and not sensitive to parameters selection. For Chinese, our model surpasses Li *et al.* [21] by a margin of 1.9%.

We further investigate the effects of hash generation setting on the overall performance of SRL. Figure 4 and 5 show how SRL score changes with the number of importance parameters and hash pool size. Figures depict that increasing the number of importance parameters and hash pool size does not guarantee a performance boost, however increasing it beyond a certain threshold can affect the model performance. The optimal value of *importance parameter* is 5 and for hash pool size is 20. These findings also confirm that there may exist many redundant parameters in deep neural networks and we can improve the model training speed by selecting important parameters without hurting the model performance. The difference between full and hash generation techniques is less than 0.3%. The full generation method performs better than the hash generation method as depicted in the results. But the hash generation method is efficient than the full generation in terms of the model size. Results of the proposed model on both in domain and out of domain datasets show the effectiveness and learning capability of the model.

## B. CoNLL-2008 SRL setting

CoNLL-2009 includes gold predicates beforehand, but predicate identification is an indispensable task for a real-world SRL system. Thus, we use our model for predicates identification and disambiguation as well and evaluate the performance on CoNLL-2008 dataset. Specifically, we use our same model as explained in Section III to identify and label predicates. The training scheme remains the same except that we remove the predicate identification flag from the input, while in inference, we perform an additional procedure to identify all

 TABLE III

 Results on the Conll-2008 English in domain (WSJ) dataset and English out of domain (Brown) dataset.

System	English WSJ			English Brown		
System	Р	R	$F_1$	Р	R	$F_1$
Johansson and Nugues [8]	_	_	81.7	_	_	69.0
Zhao et al. [32]	_	_	82.1	_	_	_
Zhao et al. [36]	_	_	82.5	_	_	_
He et al. [67]	83.9	82.7	83.3	_	_	_
Li et al. [9]	84.5	86.1	85.3	74.6	73.8	74.2
(Ours) SRL-CNN full	85.6	84.4	85.0	74.2	73.8	74.0
(Ours) SRL-CNN hash	84.5	85.3	84.9	73.9	73.5	73.7
(Ours) SRL-DPCNN full	85.0	85.4	85.2	74.3	73.9	74.1
(Ours) SRL-DPCNN hash	84.4	84.2	84.3	73.5	74.3	73.9
(Ours) SRL-DenseCNN full	85.8	84.4	85.1	74.6	74.8	74.7
(Ours) SRL-DenseCNN hash	84.8	84.6	84.7	74.0	74.4	74.2



Fig. 4.  $F_1$  on English test dataset for different number of importance parameters.



Fig. 5.  $F_1$  on English test dataset for different hash pool sizes.

the predicates in a given sentence. The arguments labeling is done in a similar way as in CoNLL-2009 setting.

The overall results on English in-domain (WSJ) and out-ofdomain (Brown) test sets are shown in Table III. On English in-domain test set, our SRL-DPCNN *full* gives  $F_1$  score of 85.2% which is comparable with the best performing model of Li *et al.* [9] (85.3%  $F_1$ ). On English out-of-domain test set, our SRL-DenseCNN *full* gives the best performance (74.7%  $F_1$ ).

## C. Ablation study

We perform a series of ablation studies on CoNLL-2009 English test dataset to analyze the model.

TABLE IV  $\Delta F_1$  represents the performance difference between syntax aware and syntax agnostic models.

System	w/o syntax	with syntax	$\Delta F_1$
Marcheggiani and Titov [23]	87.7	88.0	0.3
He et al. [67]	88.7	89.5	0.8
Cai et al. [60]	89.6	89.6	0
Li et al. [21]	88.7	89.8	1.1
Li et al. [9]	90.4	90.4	0
Ours SRL-DenseCNN full	90.0	90.9	0.9

TABLE V Ablation study to compare the effects of adaptive convolution in SRL system.

Our system	Р	R	$F_1$
Ours (syntax-agnostic)	90.7	89.3	90.0
w/o adaptive convolution	90.0	87.8	88.9
Ours (with GCN)	90.2	88.6	89.9
Marcheggiani and Titov [23]	89.1	86.8	88.0
SRL-DenseCNN full	91.2	90.6	90.9

Word representation: To interpret the importance of word embedding learned by our model, we carry out experiments with different input settings. Table VI shows how our model performs without POS tags information, ELMo embeddings, lemma embeddings  $(x^l)$ , pre-trained embeddings  $(x^p)$  and randomly initialized embeddings  $(x^r)$ . The effect of POS tags on the overall performance of our model is 0.8% in terms of F<sub>1</sub> score, which is still better than most of the previous approaches published. The absence of ELMo embedding degrades the performance by 1.2%. However, the absence of one of the randomly initialized lemma and word embeddings and pretrained word embeddings has comparatively less impact on the overall performance of our model. These results depict that the presence of these features can enhance the overall

 TABLE VI

 Ablation study on CoNLL-2009 English test dataset.

Our system	Р	R	$F_1$
SRL-DenseCNN full	91.2	90.6	90.9
w/o POS tags	91.1	89.2	90.1
w/o ELMo embedding	90.5	88.9	89.7
w/o randomly initialized $(x^r)$	91.2	90.2	90.7
w/o pre-trained $(x^p)$	91.1	89.9	90.5
w/o lemma $(x^l)$	90.0	91.4	90.7



Fig. 6.  $F_1$  on English test dataset with different number of filters, x-axis is in logarithmic scale.



Fig. 7.  $F_1$  on English test dataset for different depths.

SRL performance but our model still provides comparatively better results even in the absence of these features.

Adaptive vs non-adaptive convolution: To verify the effectiveness of adaptive convolution, we compare its performance with varying number of filters (Figure 6) and depths (Figure 7). We further show how the performance varies if we replace adaptive convolution with non-adaptive convolution where filters are not generated dynamically based on the inputs. As can be observed in Figure 6, adaptive CNN provides a performance stability for different number of filters as compared to nonadaptive CNN. Furthermore, the performance of non-adaptive CNN drastically decreases with less number of filters. The performance of non-adaptive CNN with 2 filters is 8.3% less as compared to that with 100 filters. However, the performance of adaptive CNN with 2 number of filters decreases by 0.7% only as compared to that with 100 filters.

We see a similar performance variation tendency on depths as can be seen in Figure 7. The performance of adaptive DPCNN with depth 3 is only 0.6% less as compared to non-adaptive DPCNN with the best performing depths. This confirms that by using dynamically generated filters, our model can capture the necessary information related to SRL. Adaptive convolution can extract SRL related features with only few filters and shallow depths. This also helps in mitigating the required effort to tune hyperparameters for adaptive convolution.

Table VIII shows that the filter generation by using the full generation method results in a quadratic increase in the number parameters as compared to the hash generation method. The number of parameters in the hash generation method is still larger than that of non-adaptive convolution. But the performance gain of adaptive convolution over non-adaptive convolution is not owing to this increase in the number of parameters. This can be verified by the fact that increasing the number of filters and depth (for non-adaptive convolution) beyond a certain value does not have any impact on model performance. As shown in Figure 6, increasing the number of filters beyond 100 for non-adaptive CNN does not increase performance. Similarly, increasing depth beyond 9 for nonadaptive DenseCNN has no effect on the overall performance (Figure 7). The performance of non-adaptive DPCNN rather decreases when depth is increased beyond 10. This validates that the gain in overall SRL performance is owing to the effectiveness of adaptive convolution, instead of the increased number of parameters.

**Deep encoding effect:** Table IV shows the comparison of our SRL-DenseCNN *full* with Marcheggiani and Titov [23], He *et al.* [67], Cai *et al.* [60], Li *et al.* [21] and Li *et al.* [9]. The reported results are on CoNLL-2009 English test dataset under syntax-aware and syntax agnostic environments. The results show that our model gives better performance improvement with the integration of syntax information as compared to the previous best models.

To further analyze if adaptive convolution helps in the effective encoding of syntactic information, we compare our model with three syntax-aware versions. In these experiments, we use the same encoder as Marcheggiani and Titov [23].

• Our proposed model without adaptive convolution.

• Replace Tree-LSTM with graph convlotion layer (GCN) as proposed by Marcheggiani and Titov [23] (i.e. essentially adding adaptive convolution layer above GCN in Marcheggiani and Titov [23]).

• Replace Tree-LSTM with graph convlotion layer (GCN) and remove adaptive convolution (i.e. essentially the model of Marcheggiani and Titov [23]).

The results of these experiments are shown in Table V. As expected, the removal of the adaptive convolution layer results in the performance decline by 2.0%. However, the inclusion of adaptive convolution above GCN in Marcheggiani and Titov [23] results in their model's performance improvement by 1.9%. This performance improvement demonstrates the effectiveness of adaptive convolution which uses dynamically generated filters for capturing information that needs to be disambiguated given the current inputs.

**Syntactic input:** To investigate how the quality of syntactic input affects the SRL performance, we use 4 types of syntactic inputs in our model. 1) predicated parses officially given in CoNLL-2009. 2) Biaffine parser. 3) BIST parser [72]. 4) gold parses given in CoNLL-2009 dataset.

For comparison, we use semantic labeled  $F_1$  as an evaluation metric for SRL performance, labeled attachment score (LAS) to quantify parse quality and Sem-F<sub>1</sub>/LAS as an

#### TABLE VII

Results on the CoNLL-2009 English test dataset for labeled attachment score (LAS), precision (P), recall (R), semantic labeled score ( $F_1$ ) and Sem- $F_1$ / LAS ratio. We use our SRL-DenseCNN *full* model for comparison.

System	LAS	Р	R	Sem-F <sub>1</sub>	Sem-F <sub>1</sub> / LAS
Zhao et al. [33] [SRL-only]	86.0	_	_	85.4	99.3
Zhaoet al. [13] [Joint]	89.2	_	_	86.2	96.6
Björkelund et al. [68]	89.8	87.1	84.5	85.8	95.6
Lei et al. [58]	90.4	_	_	86.6	95.8
Roth and Lapata [61]	89.8	88.1	85.3	86.7	96.5
Marcheggiani and Titov [23]	90.34	89.1	86.8	88.0	97.41
He et al. [67] [CoNLL-2009 predicted]	86.0	89.7	89.3	89.5	104.0
He et al. [67] [Gold syntax]	100	91.0	89.7	90.3	90.3
Li et al. [21] [CoNLL-2009 predicted]	86.0	90.5	88.5	89.5	104.7
Li et al. [21] [Gold syntax]	100	91.0	90.0	90.5	90.50
Ours [CoNLL-2009 predicted]	86.0	91.2	90.6	90.9	105.6
Ours [CoNLL-2009 Biaffine parser]	90.22	91.3	90.7	91.0	100.9
Ours [BIST parser]	90.05	91.1	90.8	90.9	101.0
Ours <i>full</i> [Gold Syntax]	100	91.4	91.0	91.2	91.2

TABLE VIII NUMBER OF PARAMETERS IN EACH MODEL. THE INPUT EMBEDDINGS ARE NOT INCLUDED IN THE PARAMETERS COUNT.

	CNN	DPCNN	DenseCNN
Non-adaptive	0.6M	3.5M	2.7M
Hashed generation	12.9M	45M	77M
Full Generation	316.7M	320.4M	383.3M

TABLE IX Result with different pretrained language models.

System	Р	R	$F_1$
SRL-DenseCNN hash	90.6	90.8	90.7
BERTBASE	91.2	90.4	90.8
BERTLARGE	91.1	90.9	91.0
XLNET <sub>BASE</sub>	90.7	91.3	91.0
XLNET <sub>LARGE</sub>	91.5	90.9	91.2

additional metric for comparison as given by CoNLL-2008 shared task<sup>3</sup> [10].

Table VII shows that the performance of our model is quite stable with the varying quality of syntactic parses. Secondly, the ratio  $F_1/LAS$  decreases with the increasing quality of the syntactic parse. Thirdly, when LAS reaches 100% for syntactic parse,  $F_1/LAS$  ratio of our model becomes 91.2%, advocating the strength of our model. The last conclusion to be drawn from the comparison is that the high quality syntax information can boost SRL performance which lines up with the conclusion drawn by Li *et al.* [21] and He *et al.* [18].

**Replacing ELMo with other language models:** Lastly, we replace ELMo embeddings in the input with other pre-trained language models like BERT [73] and XLNET [74] to see if our model can achieve further performance improvement. We use our SRL-DenseCNN *hash* model for this experiment on CoNLL-2009 test dataset. The results are shown in Table IX. Both BERT and XLNET help the model to improve the performance over ELMo embeddings for the concerned task. One possible reason behind this improvement is the ability of BERT and XLNET to provide more accurate context

<sup>3</sup>CoNLL-2008 task is only for English, while CoNLL-2009 is a multilingual task. The main difference is that predicates are pre-identified for the latter.

information from the text. Furthermore, XLNET embeddings help the model to gain 0.5% improvement as compared to 0.3% improvement with BERT embeddings.

### V. CONCLUSION

This paper presents a neural framework for semantic role labeling, effectively incorporating a filter generation network to extract important syntactic features encoded by BiLSTM and Tree-LSTM by generating filters conditioned on inputs. The adaptive convolution endows flexibility to existing convolution operations. With the extraction of important syntax information, we are able to enlarge the gap between syntax aware and syntax agnostic SRL systems. We further study a hashing technique which drastically decreases the size of the filter generation network. Lastly, we explore the effects of syntax quality on SRL systems and conclude that the high quality syntax can improve SRL performance. Experiments on CoNLL-2009 dataset validate that our proposed model outperforms most previous SRL systems for both English and Chinese languages.

### REFERENCES

- D. Gildea and D. Jurafsky, "Automatic labeling of semantic roles," Computational linguistics, vol. 28, no. 3, pp. 245–288, 2002.
- [2] C. Shi, S. Liu, S. Ren, S. Feng, M. Li, M. Zhou, X. Sun, and H. Wang, "Knowledge-based semantic embedding for machine translation," in Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL) (Volume 1: Long Papers), 2016, pp. 2245– 2254.
- [3] M. Surdeanu, S. Harabagiu, J. Williams, and P. Aarseth, "Using predicate-argument structures for information extraction," in *Proceed*ings of the 41st Annual Meeting of the Association for Computational Linguistics (ACL), 2003, pp. 8–15.
- [4] J. Berant, A. Chou, R. Frostig, and P. Liang, "Semantic parsing on freebase from question-answer pairs," in *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing* (*EMNLP*), 2013, pp. 1533–1544.
- [5] W.-t. Yih, M. Richardson, C. Meek, M.-W. Chang, and J. Suh, "The value of semantic parse labeling for knowledge base question answering," in *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL) (Volume 2: Short Papers)*, 2016, pp. 201–206.
- [6] C.-H. Wu, Z.-J. Chuang, and Y.-C. Lin, "Emotion recognition from text using semantic labels and separable mixture models," *ACM transactions* on Asian language information processing (TALIP), vol. 5, no. 2, pp. 165–183, 2006.

- [7] S. Yan and X. Wan, "Srrank: leveraging semantic roles for extractive multi-document summarization," *IEEE/ACM Transactions on audio*, *speech, and language processing*, vol. 22, no. 12, pp. 2048–2058, 2014.
- [8] R. Johansson and P. Nugues, "Dependency-based syntactic-semantic analysis with propbank and nombank," in *CoNLL 2008: proceedings* of the twelfth conference on computational natural language learning, 2008, pp. 183–187.
- [9] Z. Li, S. He, H. Zhao, Y. Zhang, Z. Zhang, X. Zhou, and X. Zhou, "Dependency or span, end-to-end uniform semantic role labeling," in *Proceedings of the Thirty-third Conference of the Association for the Advancement of Artificial Intelligence (AAAI)*, vol. 33, 2019, pp. 6730– 6737.
- [10] M. Surdeanu, R. Johansson, A. Meyers, L. Màrquez, and J. Nivre, "The conll 2008 shared task on joint parsing of syntactic and semantic dependencies," in *Proceedings of the Twelfth Conference on Computational Natural Language Learning - Shared Task (CoNLL)*, 2008, pp. 159–177.
- [11] J. Hajič, M. Ciaramita, R. Johansson, D. Kawahara, M. A. Martí, L. Màrquez, A. Meyers, J. Nivre, S. Padó, J. Štepánek *et al.*, "The conll-2009 shared task: Syntactic and semantic dependencies in multiple languages," in *Proceedings of the Thirteenth Conference on Computational Natural Language Learning (CoNLL 2009):Shared Task*, 2009, pp. 1–18.
- [12] S. Pradhan, W. Ward, K. Hacioglu, J. H. Martin, and D. Jurafsky, "Semantic role labeling using different syntactic views," in *Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics* (ACL), 2005, pp. 581–588.
- [13] H. Zhao, W. Chen, K. Uchimoto, K. Torisawa et al., "Multilingual dependency learning: Exploiting rich features for tagging syntactic and semantic dependencies," in Proceedings of the Thirteenth Conference on Computational Natural Language Learning (CoNLL 2009): Shared Task, 2009, pp. 61–66.
- [14] H. Bai and H. Zhao, "Deep enhanced representation for implicit discourse relation recognition," in *Proceedings of the 27th International Conference on Computational Linguistics (COLING 2018)*, 2018.
- [15] Z. Zhang and H. Zhao, "One-shot learning for question-answering in gaokao history challenge," in *Proceedings of the 27th International Conference on Computational Linguistics (COLING 2018)*, 2018.
- [16] V. Punyakanok, D. Roth, and W.-t. Yih, "The importance of syntactic parsing and inference in semantic role labeling," *Computational Linguistics*, vol. 34, no. 2, pp. 257–287, 2008.
- [17] J. Zhou and W. Xu, "End-to-end learning of semantic role labeling using recurrent neural networks," in *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics (ACL)*), 2015, pp. 1127–1137.
- [18] L. He, K. Lee, M. Lewis, and L. Zettlemoyer, "Deep semantic role labeling: What works and what's next," in *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (ACL)*, 2017, pp. 473–483.
- [19] D. Marcheggiani, A. Frolov, and I. Titov, "A simple and accurate syntaxagnostic neural model for dependency-based semantic role labeling," in *Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017)*, 2017.
- [20] D. Gildea and M. Palmer, "The necessity of parsing for predicate argument recognition," in *Proceedings of the 40th annual meeting on Association for Computational Linguistics (ACL)*, 2002, pp. 239–246.
- [21] Z. Li, S. He, J. Cai, Z. Zhang, H. Zhao, G. Liu, L. Li, and L. Si, "A unified syntax-aware framework for semantic role labeling," in *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 2018, pp. 2401–2411.
- [22] F. Qian, L. Sha, B. Chang, L.-c. Liu, and M. Zhang, "Syntax aware lstm model for semantic role labeling," in *Proceedings of the 2nd Workshop* on Structured Prediction for Natural Language Processing, 2017, pp. 27–32.
- [23] D. Marcheggiani and I. Titov, "Encoding sentences with graph convolutional networks for semantic role labeling," in *Proceedings of the* 2017 Conference on Empirical Methods in Natural Language Processing (EMNLP), 2017, pp. 1506–1515.
- [24] Y. Kim, "Convolutional neural networks for sentence classification," in Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), 2014, pp. 1746–1751.
- [25] R. Johnson and T. Zhang, "Deep pyramid convolutional neural networks for text categorization," in *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (ACL)*, 2017, pp. 562–570.
- [26] S. Wang, M. Huang, and Z. Deng, "Densely connected cnn with multi-scale feature attention for text classification." in *Proceedings of International Joint Conference on Artificial Intelligence (IJCAI)*, 2018, pp. 4468–4474.

- [27] E. Cakır, G. Parascandolo, T. Heittola, H. Huttunen, and T. Virtanen, "Convolutional recurrent neural networks for polyphonic sound event detection," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 25, no. 6, pp. 1291–1303, 2017.
- [28] O. Abdel-Hamid, A.-r. Mohamed, H. Jiang, L. Deng, G. Penn, and D. Yu, "Convolutional neural networks for speech recognition," *IEEE/ACM Transactions on audio, speech, and language processing*, vol. 22, no. 10, pp. 1533–1545, 2014.
- [29] K. S. Tai, R. Socher, and C. D. Manning, "Improved semantic representations from tree-structured long short-term memory networks," in Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (ACL-IJCNLP), 2015, pp. 1556–1566.
- [30] B.-J. Choi, J.-H. Park, and S. Lee, "Adaptive convolution for text classification," in *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL:HLT)*, 2019, pp. 2475–2485.
- [31] H. Zhao and C. Kit, "Parsing syntactic and semantic dependencies with two single-stage maximum entropy models," in *Proceedings of* the Twelfth Conference on Computational Natural Language Learning (CoNLL), 2008, pp. 203–207.
- [32] H. Zhao, W. Chen, and C. Kit, "Semantic dependency parsing of nombank and propbank: An efficient integrated approach via a large-scale feature selection," in *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Association for Computational Linguistics, 2009, pp. 30–39.
- [33] H. Zhao, W. Chen, C. Kit, and G. Zhou, "Multilingual dependency learning: A huge feature engineering method to semantic dependency parsing," in *Proceedings of the Thirteenth Conference on Computational Natural Language Learning - Shared Task (CoNLL)*, 2009, pp. 55–60.
- [34] J. Li, G. Zhou, H. Zhao, Q. Zhu, and P. Qian, "Improving nominal srl in chinese language with verbal srl information and automatic predicate recognition," in *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing (EMNLP): Volume 3-Volume* 3, 2009, pp. 1280–1288.
- [35] A. Björkelund, L. Hafdell, and P. Nugues, "Multilingual semantic role labeling," in Proceedings of the Thirteenth Conference on Computational Natural Language Learning - Shared Task (CoNLL), 2009, pp. 43–48.
- [36] H. Zhao, X. Zhang, and C. Kit, "Integrative semantic dependency parsing via efficient large-scale feature selection," *Journal of Artificial Intelligence Research*, vol. 46, pp. 203–233, 2013.
- [37] H. Yang and C. Zong, "Learning generalized features for semantic role labeling," ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP), vol. 15, no. 4, pp. 1–16, 2016.
- [38] W. Che, M. Zhang, A. Aw, C. Tan, T. Liu, and S. Li, "Using a hybrid convolution tree kernel for semantic role labeling," ACM Transactions on Asian Language Information Processing (TALIP), vol. 7, no. 4, pp. 1–23, 2008.
- [39] J. Li and G. Zhou, "Unified semantic role labeling for verbal and nominal predicates in the chinese language," ACM Transactions on Asian Language Information Processing (TALIP), vol. 10, no. 3, pp. 1–21, 2011.
- [40] H. Yang, Y. Zhou, and C. Zong, "Bilingual semantic role labeling inference via dual decomposition," ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP), vol. 15, no. 3, pp. 1–21, 2016.
- [41] Z. Zhang, H. Zhao, and L. Qin, "Probabilistic graph-based dependency parsing with convolutional neural network," in *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL)* (Volume 1: Long Papers), 2016, pp. 1382–1392.
- [42] D. Cai and H. Zhao, "Neural word segmentation learning for chinese," in Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL) (Volume 1: Long Papers), 2016, pp. 409–420.
- [43] L. Qin, Z. Zhang, and H. Zhao, "Implicit discourse relation recognition with context-aware character-enhanced embeddings," in *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*, 2016, pp. 1914–1924.
- [44] R. Wang, H. Zhao, B.-L. Lu, M. Utiyama, and E. Sumita, "Connecting phrase based statistical machine translation adaptation," in *Proceedings* of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers, 2016, pp. 3135–3145.
- [45] R. Wang, H. Zhao, S. Ploux, B.-L. Lu, and M. Utiyama, "A bilingual graph-based semantic model for statistical machine translation." in *Proceedings of International Joint Conference on Artificial Intelligence* (*IJCAI*), 2016, pp. 2950–2956.

- [46] Z. Zhang, Y. Huang, and H. Zhao, "Subword-augmented embedding for cloze reading comprehension," in *Proceedings of the 27th International Conference on Computational Linguistics*, 2018, pp. 1802–1814.
- [47] Z. Li, J. Cai, S. He, and H. Zhao, "Seq2seq dependency parsing," in Proceedings of the 27th International Conference on Computational Linguistics, 2018, pp. 3203–3214.
- [48] Y. Huang, Z. Li, Z. Zhang, and H. Zhao, "Moon ime: neural-based chinese pinyin aided input method with customizable association," in *Proceedings of ACL 2018, System Demonstrations*, 2018, pp. 140–145.
- [49] Q. T. N. Do, S. Bethard, and M.-F. Moens, "Domain adaptation in semantic role labeling using a neural language model and linguistic resources," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 23, no. 11, pp. 1812–1823, 2015.
- [50] M. Sundermeyer, H. Ney, and R. Schlüter, "From feedforward to recurrent lstm neural networks for language modeling," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 23, no. 3, pp. 517–529, 2015.
- [51] C. Guan, Y. Cheng, and H. Zhao, "Semantic role labeling with associated memory network," in *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL:HLT)*, 2019, pp. 3361–3371.
- [52] S. He, Z. Li, and H. Zhao, "Syntax-aware multilingual semantic role labeling," in *Proceedings of the 2019 Conference on Empirical Methods* in Natural Language Processing (EMNLP), 2019, pp. 5353–5362.
- [53] Z. Li, H. Zhao, R. Wang, and K. Parnow, "High-order semantic role labeling," arXiv preprint arXiv:2010.04641, 2020.
- [54] J. Zhou, Z. Li, and H. Zhao, "Parsing all: Syntax and semantics, dependencies and spans," arXiv preprint arXiv:1908.11522, 2019.
- [55] Z. Li, C. Guan, H. Zhao, R. Wang, K. Parnow, and Z. Zhang, "Memory network for linguistic structure parsing," *IEEE/ACM Transactions on Audio, Speech, and Language Processing (TASLP)*, vol. 28, pp. 2743– 2755, 2020.
- [56] W. Foland and J. H. Martin, "Dependency-based semantic role labeling using convolutional neural networks," in *Proceedings of the Fourth Joint Conference on Lexical and Computational Semantics*, 2015, pp. 279– 288.
- [57] N. FitzGerald, O. Täckström, K. Ganchev, and D. Das, "Semantic role labeling with neural network factors," in *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing* (*EMNLP*), 2015, pp. 960–970.
- [58] T. Lei, Y. Zhang, L. Marquez, A. Moschitti, and R. Barzilay, "High-order low-rank tensors for semantic role labeling," in *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL:HLT)*, 2015, pp. 1150–1160.
- [59] Z. Tan, M. Wang, J. Xie, Y. Chen, and X. Shi, "Deep semantic role labeling with self-attention," in *Proceedings of the Thirty-Second Conference of the Association for the Advancement of Artificial Intelligence* (AAAI), 2018.
- [60] J. Cai, S. He, Z. Li, and H. Zhao, "A full end-to-end semantic role labeler, syntax-agnostic over syntax-aware?" in *Proceedings of the 27th International Conference on Computational Linguistics*, 2018, pp. 2753– 2765.
- [61] M. Roth and M. Lapata, "Neural semantic role labeling with dependency path embeddings," in *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL)*, 2016, pp. 1192–1202.
- [62] X. Zhang, J. Zhao, and Y. LeCun, "Character-level convolutional networks for text classification," in *Proceedings of the Advances in neural information processing systems (NIPS)*, 2015, pp. 649–657.
- [63] M. E. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer, "Deep contextualized word representations," in *Proceedings of the 2018 Conference of the North American Chapter* of the Association for Computational Linguistics: Human Language Technologies (NAACL: HLT), 2018.
- [64] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [65] Z. Lin, M. Feng, C. N. d. Santos, M. Yu, B. Xiang, B. Zhou, and Y. Bengio, "A structured self-attentive sentence embedding," in *International Conference on Learning Representations (ICLR)*, 2017.
- [66] D. Tito Svenstrup, J. Hansen, and O. Winther, "Hash embeddings for efficient word representations," *Advances in neural information* processing systems (NIPS), vol. 30, pp. 4928–4936, 2017.
- [67] S. He, Z. Li, H. Zhao, and H. Bai, "Syntax for semantic role labeling, to be, or not to be," in *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (ACL) (Volume 1: Long Papers)*, 2018, pp. 2061–2071.

- [68] A. Björkelund, B. Bohnet, L. Hafdell, and P. Nugues, "A highperformance syntactic and semantic dependency parser," in *Proceedings* of the 23rd International Conference on Computational Linguistics (COLING), 2010, pp. 33–36.
- [69] J. Pennington, R. Socher, and C. D. Manning, "Glove: Global vectors for word representation," in *Proceedings of the 2014 conference on Empirical Methods in Natural Language Processing (EMNLP)*, 2014, pp. 1532–1543.
- [70] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, "Distributed representations of words and phrases and their compositionality," in *Advances in Neural Information Processing Systems (NIPS)*, 2013, pp. 3111–3119.
- [71] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in *Proceedings of the 3rd International Conference on Learning Representations (ICLR)*, 2014.
- [72] E. Kiperwasser and Y. Goldberg, "Simple and accurate dependency parsing using bidirectional lstm feature representations," *Transactions* of the Association for Computational Linguistics, vol. 4, pp. 313–327, 2016.
- [73] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," *arXiv* preprint arXiv:1810.04805, 2018.
- [74] Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. R. Salakhutdinov, and Q. V. Le, "Xlnet: Generalized autoregressive pretraining for language understanding," in *Advances in neural information processing systems* (*NIPS*), 2019, pp. 5753–5763.



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