Syntax Aware LSTM Model for Chinese Semantic Role Labeling

Feng Qian, Lei Sha, Baobao Chang, Lu-chen Liu, Ming Zhang

Abstract
As for semantic role labeling (SRL) task, when it comes to utilizing parsing information, both traditional methods and recent recurrent neural network (RNN) based methods use the feature engineering way. In this paper, we propose Syntax Aware Long Short Time Memory (SA-LSTM). The structure of SA-LSTM modifies according to dependency parsing information in order to model parsing information directly in an architecture engineering way instead of feature engineering way. We experimentally demonstrate that SA-LSTM gains more improvement from the model architecture. Furthermore, SA-LSTM outperforms the state-of-the-art on CPB 1.0 significantly according to Student t-test ($p < 0.05$).

1 Introduction
The task of SRL is to recognize arguments of a given predicate in a sentence and assign semantic role labels. Since SRL can give a lot of semantic information, and can help in sentence understanding, a lot of NLP works such as machine translation (Xiong et al., 2012; Aziz et al., 2011) use SRL information. Figure 1 shows an example of SRL task from Chinese Proposition Bank 1.0 (CPB 1.0) (Xue and Palmer, 2003).

Traditional methods on SRL use statistical classifiers such as CRF, MaxEntropy and SVM (Sun and Jurafsky, 2004; Xue, 2008; Ding and Chang, 2008, 2009; Sun, 2010) to do classification according to manually designed features.

Recent works based on recurrent neural network (Collobert and Weston, 2008; Zhou and Xu, 2015; Wang et al., 2015) extract features automatically, and outperform traditional methods significantly. However, RNN methods treat language as sequence data, so most of them fail to take tree structured parsing information into account, which is considered important for SRL task (Xue, 2008; Punyakanok et al., 2008; Pradhan et al., 2005). Even though there are some RNN based works trying to utilize parsing information, they still do it in a feature-engineering way.

We propose Syntax Aware LSTM (SA-LSTM) to directly model complex dependency parsing information in an architecture engineering way instead of feature engineering way. For example, in Figure 1, the arrowed line stands for dependency relationship, which is rich in syntactic information. Our SA-LSTM architecture is shown in Figure 2. Compares to ordinary LSTM, we add additional connections between dependency related words to capture and model such rich syntactic information in architecture engineering way. Also, to take dependency relationship type into account, we also introduce trainable weights for different types of dependency relationship. The weights can be trained to indicate importance of a dependency type.

Figure 1: A sentence from CPB with semantic role label and dependency parsing information

We experimentally demonstrate that SA-LSTM utilizes parsing information better than traditional feature engineering way. Furthermore, SA-LSTM reaches 79.64% $F_1$ score on CPB 1.0, outperforms the state-of-the-art significantly based on Student’s t-test ($p < 0.05$).

2 Syntax Aware LSTM
Compares to traditional feature engineering method, RNN-LSTM alleviates the burden of manual feature design and selection. However,
Figure 2: SA-LSTM architecture: A ⃝ stands for one word. The dotted arrows stand for original neighbor connections of bi-LSTM. Solid arrows stand for dependency relationship connections. Note that though dependency parsing relationship is directed, we here treated them as undirected. We only consider whether there is a connection, and the connection type.

most RNN-LSTM based methods failed to utilize dependency parsing relationship. Based on bi-RNN-LSTM, we propose SA-LSTM which keeps all the merit points of bi-RNN-LSTM, and at the same time can model dependency parsing information directly.

2.1 Conventional bi-LSTM Model for SRL

In a sentence, each word \( w_t \) has a feature representation \( x_t \) which is generated automatically as (Wang et al., 2015) did. \( z_t \) is feature embedding for \( w_t \), calculated as followed:

\[
z_t = f(W_1 x_t)
\]

where \( W_1 \in \mathbb{R}^{n_1 \times n_0} \), \( n_0 \) is the length of word feature representation.

In a sentence, each word \( w_t \) has six internal vectors, \( \tilde{C}, g_i, g_f, g_o, C_t, \) and \( h_t \), shown in Equation 2:

\[
\begin{align*}
\tilde{C} &= f(W_c z_t + U_c h_{t-1} + b_c) \\
g_j &= \sigma(W_j z_t + U_j h_{t-1} + b_j) \quad j \in \{i, f, o\} \\
C_t &= g_i \odot \tilde{C} + g_f \odot C_{t-1} \\
h_t &= g_o \odot f(C_t)
\end{align*}
\]

where \( \tilde{C} \) is the candidate value of the current cell state. \( g \) are gates used to control the flow of information. \( C_t \) is the current cell state. \( h_t \) is hidden state of \( w_t \). \( W_c \) and \( U_c \) are matrices used in linear transformation:

\[
W_x, x \in \{c, i, f, o\} \in \mathbb{R}^{n_h \times n_1} \\
U_x, x \in \{c, i, f, o\} \in \mathbb{R}^{n_h \times n_h}
\]

As convention, \( f \) stands for \( \text{tanh} \) and \( \sigma \) stands for \( \text{sigmoid} \). \( \odot \) means the element-wise multiplication.

In order to make use of bidirectional information, the forward \( \overrightarrow{h_t} \) and backward \( \overleftarrow{h_t} \) are concatenated together, as shown in Equation 4:

\[
a_t = [\overrightarrow{h_t}, \overleftarrow{h_t}]
\]

Finally, \( o_t \) is the result vector with each dimension corresponding to the score of each semantic role tag, and are calculated as shown in Equation 5:

\[
o_t = W_3 f(W_2 a_t)
\]

where \( W_2 \in \mathbb{R}^{n_3 \times n_2} \), \( n_2 \) is \( 2 \times h_t \), \( W_3 \in \mathbb{R}^{n_4 \times n_3} \) and \( n_4 \) is the number of tags in IOBES tagging schema.

2.2 Syntax Aware LSTM Model for SRL

Structure of our SA-LSTM is shown in Figure 3. The most significant change we make to the original RNN-LSTM is shown in the shaded area.

Figure 3: Cell Structure of Syntax Aware LSTM

\( S_t \) is the syntax information input into current cell, and is calculated as shown in Equation 6:

\[
S_t = f(\sum_{i=0}^{t-1} \alpha \times h_i)
\]

\( \alpha = \begin{cases} 
1 & \text{If there exists dependency relationship between } w_i \text{ and } w_t \\
0 & \text{Otherwise}
\end{cases} \) (7)

\( S_t \) is the weighted sum of all hidden state vectors \( h_i \) which come from previous words \( w_i \). Note
that, $\alpha \in \{0, 1\}$ indicates whether there is a dependency relationship between $w_i$ and $w_t$, only dependency related $h_i$ can be input into current cell.

We add a gate $g_s$ to constrain information from $S_t$, as shown in Equation 8. To protect the original sentence information from being diluted (Wu et al., 2016) by $S_t$, we add $S_t$ to hidden layer vector $h_t$ instead of adding to cell state $C_t$, as shown in Equation 9:

$$ g_s = \sigma(W_s z_t + U_s h_{t-1} + b_s) \quad (8) $$

So $h_t$ in our SA-LSTM cell is calculated as:

$$ h_t = g_o \odot f(C_t) + g_s \odot S_t \quad (9) $$

SA-LSTM changes structure by adding different connections according to dependency parsing information. In this way, we consider the whole structure of dependency tree into SA-LSTM in an architecture engineering way.

However, by using $\alpha$ in Equation 7, we do not take dependency type into account, so we further improve the way $\alpha$ is calculated from Equation 7 to Equation 10. Each $type_m$ of dependency relationship is assigned a trainable weight $\alpha_m$. In this way SA-LSTM can model differences between types of dependency relationship.

$$ \alpha = \begin{cases} 
\alpha_m & \text{If there exists type}_m \text{ dependency relationship between } w_i \text{ and } w_t \\
0 & \text{Otherwise} 
\end{cases} \quad (10) $$

### 2.3 Training Criteria

We use maximum likelihood criterion to train our model. Stochastic gradient ascent algorithm is used to optimize the parameters. Global normalization is applied.

Given a training pair $T = (x, y)$ where $T$ is the current training pair, $x$ denotes current the training sentence, and $y$ is the corresponding correct answer path. $y_t = k$ means that the $t$-th word has the $k$-th semantic role label. The score of $o_t$ is calculated as:

$$ s(x, y, \theta) = \sum_{i=1}^{N_t} o_{ty_i} \quad (11) $$

where $N_t$ is the word number of the current sentence and $\theta$ stands for all parameters. So the log likelihood of a single sentence is

$$ \log p(y|x, \theta) = \log \frac{\exp(s(x, y, \theta))}{\sum_y \exp(s(x, y', \theta))} \quad (12) $$

where $y'$ ranges from all valid paths of answers.

## 3 Experiment

### 3.1 Experiment setting

In order to compare with previous Chinese SRL works, we choose to do experiment on CPB 1.0. We also follow the same data setting as previous Chinese SRL work (Xue, 2008; Sun et al., 2009) did. Pre-trained\(^1\) word embeddings are tested on SA-LSTM and shows improvement.

We use Stanford Parser (Chen and Manning, 2014) to get dependency parsing information, which now supports Universal Dependency representation in Chinese. Note that the train set of the parser overlaps a part of our test set, so we re-trained the parser to avoid overlap.

Dimension of our hyper parameters are tuned according to development set and are shown in Table 1.\(^2\)

| Hyper Params | $n_1$ | $n_h$ | $n_2$ | $n_3$ | learning-rate |
|--------------|-------|-------|-------|-------|---------------|
| dim          | 200   | 100   | 200   | 100   | 0.001         |

Table 1: Hyper parameter dimensions

### 3.2 Syntax Aware LSTM Performance

| Method | $F_1 \%$ |
|--------|----------|
| Xue(2008) | 71.90   |
| Sun et al.(2009) | 74.12   |
| Yand and Zong(2014) | 75.31   |
| Wang et al.(2015)(Random Initialized) | 77.09   |
| Sha et al.(2016) | 77.69   |
| Comparison Feature Engineering Way | 77.75   |
| Our SA-LSTM(Random Initialized) | 79.56   |
| Our SA-LSTM(Pre-trained Embedding) | 79.64   |

Table 2: Results comparison on CPB 1.0

To prove that SA-LSTM gains more improvement from the new SA-LSTM architecture, than from the extra introduced parsing information, we

\(^1\)Trained by word2vec on Chinese Gigaword Corpus

\(^2\)All experiment code and related files are available on request
design a experiment in which dependency relationship is taken into account in traditional feature engineering way.

Given a word \( w_t \), \( F_t \) is the average of all dependency related \( x_i \) of previous words \( w_i \), as shown in Equation 13:

\[
F_t = \frac{1}{T} \sum_{i=0}^{t-1} \alpha \times x_i
\]

where \( T \) is the number of dependency related words and \( \alpha \) is a 0-1 variable calculated as in Equation 7.

Then \( F_t \) is concatenated to \( x_t \) to form a new feature representation. In this way, we model dependency parsing information in a conventional feature engineering way. After that, we feed these new feature representation into ordinary bi-LSTM.

As shown in Table 2, SA-LSTM reaches 79.56\% \( F_1 \) score with random initialization and 79.64\% \( F_1 \) score with pre-trained word embedding on CPB1.0 dataset. Both of them are the best \( F_1 \) score ever published on CPB 1.0 dataset.

Wang et al. (2015) used bi-LSTM without parsing information and got 77.09\% \( F_1 \) score. “comparison feature engineering method” based on his work reaches 77.75\% \( F_1 \) score. This demonstrates the introduction of dependency parsing information has impact on SRL job.

Compared with the “comparison feature engineering method” shown in table 2, it is clear that SA-LSTM gain more improvement (77.75\% to 79.56\%) from the architecture of SA-LSTM than from the introduction of extra dependency parsing information (77.09\% to 77.75\%). Indeed, it is difficult to introduce the whole tree structure into the model using the simple feature engineering way. By building the dependency relationship directly into the structure of SA-LSTM and changing the way information flows, SA-LSTM is able to consider whole tree structure of dependency parsing information.

### 3.3 Visualization of Trained Weights

According to Equation 10, influence from a single type of dependency relationship will be multiplied with type weight \( \alpha_m \). When \( \alpha_m \) is 0, the influence from this type of dependency relationship will be ignored totally. When the weight is bigger, the type of dependency relationship will have more influence on the whole system.

As shown in Figure 4, dependency relationship type \( \text{dobj} \) receives the highest weight after training, as shown by the red bar. According to grammar knowledge, \( \text{dobj} \) should be an informative relationship for SRL task, and our system give \( \text{dobj} \) the most influence automatically. This example further demonstrate that the result of SA-LSTM is highly in accordance with grammar knowledge, which further validates SA-LSTM.

### 4 Related works

Semantic role labeling (SRL) was first defined by (Gildea and Jurafsky, 2002). Early works (Gildea and Jurafsky, 2002; Sun and Jurafsky, 2004) on SRL got promising result without large annotated SRL corpus. Xue and Palmer built the Chinese Proposition Bank (Xue and Palmer, 2003) to standardize Chinese SRL research.

Traditional works such as (Xue and Palmer, 2005; Xue, 2008; Ding and Chang, 2009; Sun et al., 2009; Chen et al., 2006; Yang et al., 2014) use feature engineering methods. Traditional methods can take parsing information into account in feature engineering way, such as syntactic path feature. However, they suffer from heavy manually feature design workload, and data sparsity problem.

More recent SRL works often use neural network based methods. Collobert and Weston (2008) proposed a convolutional neural network method for SRL. Zhou and Xu (2015) proposed bidirectional RNN-LSTM method for English SRL, and Wang et al. (2015) proposed a bi-RNN-
LSTM method for Chinese SRL on which our method is based. NN based methods extract features automatically and significantly outperform traditional methods. However, most NN based methods cannot utilize parsing information which is considered important for semantic related NLP tasks (Xue, 2008; Punyakanok et al., 2008; Pradhan et al., 2005).

The work of Roth and Lapata (2016) and Sha et al. (2016) have the same motivation as ours, but in feature engineering way. Roth and Lapata (2016) embed dependency parsing path into feature representations using LSTM. Sha et al. (2016) use dependency parsing information as feature to do argument relationships classification. In contrast, LA-LSTM utilizes parsing information in an architecture engineering way, by absorbing the parsing tree structure into SA-LSTM structure.

5 Conclusion
We propose Syntax Aware LSTM model for Chinese semantic role labeling. SA-LSTM is able to model dependency information directly in an architecture engineering way. We experimentally testified that SA-LSTM gains more improvement from the SA-LSTM architecture than from the input of extra dependency parsing information. We push the state-of-the-art $F_1$ to 79.64%, which outperforms the state-of-the-art significantly according to Student t-test ($p < 0.05$).

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