Dependency Parsing with LSTMs: An Empirical Evaluation

Adhiguna Kuncoro ♠ Yuichiro Sawai ♦ Kevin Duh ♣ Yuji Matsumoto ♦
♠ School of Computer Science, Carnegie Mellon University, Pittsburgh, PA, USA
♦ Graduate School of Information Science, Nara Institute of Science and Technology, Japan
♣ HLT COE, Johns Hopkins University, Baltimore, MD, USA

akuncoro@cs.cmu.edu, {sawai.yuichiro.sn0,matsu}@is.naist.jp, kevinduh@cs.jhu.edu

Abstract

We propose a transition-based dependency parser using Recurrent Neural Networks with Long Short-Term Memory (LSTM) units. This extends the feedforward neural network parser of Chen and Manning (2014) and enables modelling of entire sequences of shift/reduce transition decisions. On the Google Web Treebank, our LSTM parser is competitive with the best feedforward parser on overall accuracy and notably achieves more than 3% improvement for long-range dependencies, which has proved difficult for previous transition-based parsers due to error propagation and limited context information. Our findings additionally suggest that dropout regularisation on the embedding layer is crucial to improve the LSTM’s generalisation.

1 Introduction

Two complementary approaches to transition-based dependency parsers have emerged recently. The feature engineering approach relies on hand-crafted feature templates to model interactions between sparse lexical features. While manually crafting these feature templates requires substantial expertise and extensive trial-and-error, this approach has led to state-of-the-art parsers in many languages (Buchholz and Marsi, 2006; Zhang and Nivre, 2011).

In contrast, the neural network approach enables automatic learning of feature combinations through non-linear hidden layers and mitigates sparsity issues by sharing similar low-dimensional distributed representations for related words (Bengio et al., 2003).

In this work, we explore new model architectures under the neural network approach. In particular, we address the issue that the feedforward architecture of the Chen and Manning parser performs training on each oracle configuration independently of one another, disregarding the fact that the oracles for each training sentence represent a whole sequence of intertwined decisions. Our proposed extension uses a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) units (Hochreiter and Schmidhuber, 1997). At each time step of the transition system, the LSTM has theoretical access to the entire history of past decisions (i.e. shift or reduce). LSTMs are naturally suited for modelling sequences and have shown promising results in e.g. machine translation (Sutskever et al., 2014) and text-vision modelling (Venugopalan et al., 2014).

We particularly focus on the LSTM’s performance in identifying long-range dependencies. Such dependencies have proved difficult for most greedy transition-based parsers (McDonald and Nivre, 2007), including our feedforward baselines, that train on each oracle independently. This difficulty can be attributed to two main reasons: 1) most long-range dependencies are ambiguous, while the classifiers only have access to a limited context window, and 2) longer arcs are constructed after shorter arcs in transition-based parsing, thus increasing the chance of error propagation. In contrast, our LSTM has the key abilities of modelling whole sequences of training oracles and memorise all past context information, both of which are likely beneficial for longer dependencies.

Despite the LSTM’s theoretical advantages, in practice it is more prone to overfitting than the feedforward architecture, even with the same number of parameters. An additional contribution of this work is an empirical investigation that suggests that dropout (Srivastava et al., 2014), particularly when applied to the embedding layer, substantially improves the LSTM’s generalisation ability regardless of hidden layer size.
2 LSTM Parsing Model

2.1 Baseline Model

Our model is an extension to Chen and Manning (2014), which uses a feedforward neural network to predict the next transition of an arc-standard system. In arc-standard, a configuration consists of a buffer $B$ (holding the input words), a stack $S$ (holding the partial parse trees), and a set of dependency arcs $A$. The parse tree is built by successively making one of these transitions:

- **SHIFT**: move the next word on $B$ to $S$
- **LEFT/RIGHT-ARC($L$)**: add left/right arc with label $L$ between two words on $S$

The features $x_t$ is a concatenation of embeddings from the top 3 words in $S$ and $B$, first and second left-right-most children of the top two words on $S$, and the leftmost of leftmost / rightmost of rightmost children of the top two words on $S$. At each configuration at time $t$, the neural network first computes the hidden layer $h_t$ from the input $x_t$ (applying a non-linear function $f$), then calculates the probability of each transition in the output vector $y_t$:

$$h_t = f(W_xhD(x_t))$$
$$y_t = \text{softmax}(W_hyD(h_t))$$

$D(\cdot)$ is a dropout operator, which randomly sets elements to 0 with probability $p_{\text{drop}}$.

2.2 Our LSTM Model

Our LSTM model (shown in Figure 1) uses the same $x_t$ features as Chen and Manning (2014), but importantly adds new inputs based on past information (such as $h_{t-1}$). The addition of previous state leads to recurrence and enables modelling and training of the entire sequence of transitions.

While recurrence may cause the “vanishing gradient” problem (Bengio et al., 1994), the LSTM architecture solves this by introducing memory cells $c_t$ that could store information over long time intervals and keep gradients from diminishing. Input gates $i_t$ control what is stored in a memory cell $c_t$, and output gates $o_t$ control whether the stored information is used in further computations. This allows information from the beginning of the sentence to influence transition actions at the end of the sentence. Forget gates $f_t$ are used to erase the information in the current memory cell.

The following equations describe our LSTM model with peephole connections (Gers et al., 2002), as set forth by Graves (2013), and apply dropout similar to Zaremba et al. (2014).

$$i_t = \sigma(W_{xi}D(x_t) + W_{ci}c_{t-1} + W_{hi}h_{t-1})$$
$$f_t = \sigma(W_{xf}D(x_t) + W_{cf}c_{t-1} + W_{hf}h_{t-1})$$
$$c_t = f_tc_{t-1} + i_t \tanh(W_{xc}D(x_t) + W_{hc}h_{t-1})$$
$$o_t = \sigma(W_{xo}D(x_t) + W_{co}c_t + W_{ho}h_{t-1})$$
$$h_t = o_t \tanh(c_t)$$
$$y_t = \text{softmax}(W_{hy}D(h_t))$$

Crucially, the LSTM not only uses input $x_t$ in its predictions for $y_t$, but also exploits values in the previous memory cell $c_{t-1}$ and hidden layer $h_{t-1}$ through the gates $i_t$, $f_t$, and $o_t$. The values of these gates are bounded between $[0, 1]$ due to the sigmoid $\sigma$, so multiplication with other components modulates what information is passed through.

Given training sentences $\{s_i\}_{i=1}^m$ with gold parse trees, our training data is a set of sequences

![Figure 1: Left: Our LSTM architecture. Right: Feedforward architecture in Chen and Manning (2014). Connections with dropout are denoted by dashed lines.](image-url)
of configurations \( c_{it} \) and oracle transition actions \( a_{it} \) at each time \( t \) for each sentence \( s_i \). We maximise the log-likelihood of the oracle transition actions \( a_{it} \) given by Equation (1), where \( \theta \) is the set of parameters including word, POS, and label embeddings, and \( y_{t}(a) \) is the probability that the parser takes transition action \( a \) at time \( t \).

\[
L(\theta) = \sum_{i=1}^{m} \sum_{t} \log y_{t}(a_{it}) - \frac{\lambda}{2} ||\theta||^2 \quad (1)
\]

We optimise by gradient backpropagation through time (BPTT) for each sentence \( s_i \), feeding the parser with gold sequence of configurations \( \{c_{it}\}_{t=1}^{\|s_i\|} \). When the parser reaches the final configuration, the gradients are backpropagated from each prediction \( y_{it} \) at time \( t \) down to time 1.

3 Experiment

3.1 Experimental Settings

We conducted the experiments on the Google Web Treebank (Petrov and McDonald, 2012), consisting of the WSJ portion of the OntoNotes corpus and five additional web domains, with 48 dependency types. The models were trained only on the training set of the WSJ corpus, while the parameters were optimised using the WSJ dev set (i.e., no tuning using any of the web domains’ dev set).

As baselines, we re-implemented the Chen and Manning parser with the same setting, including results from both the feedforward model with Tanh activation function (same activation as the LSTM) and its better-performing Cubic counterpart. Training was done for a maximum of 400 epochs, stopped early if no better dev UAS was found after 30 consecutive epochs.\(^2\)

3.2 Main Result and Analysis

The LAS result on the Google Web Treebank is summarised on Table 1, where F-T and F-C represent the feedforward baselines with Tanh and Cubic activations, respectively. Our LSTM model outperforms the feedforward baseline with the same Tanh activation function (87.5 vs 86.4 on WSJ Test), while achieving competitive accuracy with the Cubic baseline.

Table 1: Google Web Treebank LAS Result

| Dep. | F - T | F - C | LSTM |
|------|-------|-------|------|
|      | Dev   | Test  |      |
|      | 86.0  | 87.2  | 87.8 |
|      | 86.4  | 87.5  | 87.5 |

3.3 Regularisation Experiments

We discover that regularisation is important for the LSTM parser, more so than feedforward architectures. Table 3 compares the relative improvement due to dropout for feedforward vs. LSTM by constraining both models to have the same number of 500,000 parameters, corresponding to 50 hidden units for LSTM. Observe that LSTM becomes competitive only with dropout.

Table 3: Effect of Dropout on UAS Accuracy

|      | no dropout | with dropout | Δ     |
|------|------------|--------------|-------|
| F-Cubic | 89.1       | 89.5         | 0.4   |
| LSTM   | 87.4       | 89.5         | 2.1   |

To investigate what kind of dropout is beneficial, we conducted further experiments on a subset of the training data (the first 80,000 tokens of the...
The results of dropout and L-2 regularisation are in Table 4, along with the epoch where the best dev UAS is found. E-H and H-O indicate dropout between the embedding-hidden and hidden-output connections, respectively.

While dropout generally results in slower convergence, the technique outperforms L-2 and significantly improves the model’s accuracy by more than 6%. Most importantly, we found input dropout to be more crucial than hidden-output dropout and achieves the same accuracy as dropout on both input and hidden layers, suggesting that our model can achieve good accuracy with input dropout alone. We found dropout rates between 0.4 and 0.6 to be effective. Further, we found that dropout generally improves LSTMs regardless of model size. Figure 4 shows how dropout of 0.5 on E-H and E-O layers improve results for various hidden layer sizes.

### Table 4: UAS Accuracy of Various Regularisation

| RegSettings | Dev | Test | Epoch |
|-------------|-----|------|-------|
| L2 \( \lambda \) |     |      |       |
| 0           | 80.2| 80.0 | 42    |
| \( 10^{-8} \) | 80.7| 80.8 | 25    |
| \( 10^{-7} \) | 79.9| 80.3 | 43    |
| \( 10^{-6} \) | 79.8| 80.1 | 43    |
| \( 10^{-5} \) | 80.5| 80.4 | 46    |
| \( 10^{-4} \) | 83.4| 82.9 | 206   |
| \( 10^{-3} \) | 81.6| 81.6 | 159   |

| Dropout \( p_{\text{drop}} \) |     |      |       |
| E-H |     |      |       |
| 0.2 | 84.4| 84.3 | 97    |
| 0.4 | 85.8| 85.7 | 257   |
| 0.6 | \textbf{86.2} | 85.5 | 273   |
| H-O |     |      |       |
| 0.2 | 81.8| 81.6 | 52    |
| 0.4 | 82.3| 82.1 | 93    |
| 0.6 | 81.9| 81.7 | 69    |
| Both |     |      |       |
| 0.2 | 85.4| 85.0 | 122   |
| 0.4 | \textbf{86.1} | \textbf{85.9} | 315   |
| 0.6 | 85.3| 85.3 | 500   |

![Figure 2: Precision by Dependency Length](image2.png)

![Figure 3: Recall by Dependency Length](image3.png)

![Figure 4: UAS Accuracy vs Hidden Layer Size](image4.png)

### 4 Related work

Recently, various neural network models have achieved state of the art results in many parsing tasks and languages, including the Google Web Treebank dataset used in this paper. Vinyals et al. (2014) used LSTMs for sequence-to-sequence constituency parsing that makes no prior assumption of the parsing problem. For dependency parsing, Stenetorp (2013) presented an RNN compositional model, similar to the RNN constituency parser of Socher et al. (2013).

More recently, the works of Dyer et al. (2015) and Kiperwasser and Goldberg (2016) proposed transition-based LSTM models to automatically extract real-valued feature vectors from the parser configuration. The transition-based parser of Dyer et al. (2015) used a “stack LSTM” architecture and composition functions to obtain a continuous, low-dimensional representation of the stack to represent partial trees, along with the buffer and history of actions. Both our work and the stack LSTM model similarly used greedy decoding, although one primary difference is that we used the LSTM to form temporal recurrence over the hidden states\(^4\). We used the same feature extrac-

\(^3\)We used the same experimental settings as in Subsection 3.1 and evaluate UAS on the full WSJ dev and test set, with hidden layer size fixed at 60.

\(^4\)We define the hidden states as the penultimate layer right
tion template as Chen and Manning (2014) and replaced the feedforward connections with LSTM network, while Dyer et al. (2015) instead used the stack LSTM as a means to extract dense features from the parser configuration without explicit temporal recurrence.

Neural network models have also been used for structured training in transition-based parsing, achieving state of the art results on various dataset. Weiss et al. (2015) used a structured perceptron model on top of a feedforward transition-based dependency parser. When augmented with tri-training method on unlabelled data, their model achieved an impressive 87% LAS on the Web domain data of the Google Web Treebank similarly used in this work. Zhou et al. (2015) used beam search and contrastive learning to maximise the probability of the entire gold sequence with respect to all other sequences in the beam. Andor et al. (2016) similarly proposed a globally normalised model using beam search and Conditional Random Fields (CRF) loss (Lafferty, 2001) that achieved state of the art results on the benchmark English PTB dataset.

Our RNN parsing model is most similar with Xu et al. (2016) that used temporal recurrence over the hidden states for CCG parsing, although we use LSTMs instead of Elman RNNs. Our work additionally investigates the effect of dropout on model performance, and demonstrate the efficacy of temporal recurrence to better capture long-range dependencies.

## 5 Conclusions

We present a transition-based dependency parser using recurrent LSTM units. The motivation is to exploit the entire history of shift/reduce transitions when making predictions. This LSTM parser is competitive with the feedforward neural network parser of Chen and Manning (2014) on overall LAS, and notably improves the accuracy of long-range dependencies. We also show the importance of dropout, particularly on the embedding layer, in improving the model’s accuracy.

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