Joint POS Tagging and Dependency Parsing with Transition-based Neural Networks

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Abstract

Part-of-speech (POS) tagging and dependency parsing are observed to be closely related, existing work on joint modeling with manually crafted feature templates suffers from the feature sparsity and incompleteness problems. In this paper, we propose an approach to joint POS tagging and dependency parsing using transition-based neural networks. Three neural network based classifiers are designed to resolve shift/reduce, tagging, and labeling conflicts. Experiments show that our approach significantly outperforms previous methods for joint POS tagging and dependency parsing across a variety of natural languages.

1 Introduction

Part-of-speech (POS) tagging \cite{Collins2002,Toutanova2003} and dependency parsing \cite{McDonald2003,Huang2014,Dyer2015} are two fundamental tasks for understanding natural languages. While POS tagging aims to assign parts of speech to words in a text to indicate their word categories, the goal of dependency parsing is to analyze the syntactic structure of sentences by establishing relationships between words.

It is widely accepted that POS tagging and dependency parsing are closely related. On one hand, POS tagging often requires long-distance syntactic information for resolving tagging ambiguity \cite{Sun2013}. Hatori et al. \cite{Hatori2011} indicate that the disambiguation between POS tags “DEG” (a genitive marker) and “DEC” (a complementizer) for a Chinese word \textit{de} often depends on global context. On the other hand, as a pre-processing step, POS tagging directly influences the accuracy of dependency parsing significantly. For example, determining the head word of a two-word phrase “closed door” directly depends on the POS tag of “closed” (adjective or verb in past tense). Li et al. \cite{Li2011} report that dependency accuracy drops by around 6\% on Chinese when automatic POS tagging results instead of ground-truth tags are used.

Therefore, joint POS tagging and dependency parsing has attracted intensive attention in the NLP community. Previous work has focused on jointly modeling POS tagging and dependency parsing using linear models that combine both tagging and parsing features \cite{Li2011,Hatori2011,Zhang2012,Bohnet2012,Bohnet2012}. Allowing lexicality and syntax to interact in a unified framework, joint POS tagging and dependency parsing improves both tagging and parsing performance over independent models. \cite{Li2011,Hatori2011,Bohnet2012,Bohnet2012} indicate that lexicalized indicator features indispensable for discriminative dependency parsing are usually highly sparse. The situation in joint POS tagging and dependency parsing is much severer because tagging and parsing features are concatenated in joint models \cite{Li2011}. Moreover, due to the complexity of tagging and parsing natural languages, it is hard for manually-designed features to cover all regularities. As a result, the incompleteness of feature design is considered as an unavoidable issue in conventional discriminative models \cite{Chen2014}.

In this paper, we propose an approach to joint POS tagging and dependency parsing with neural networks by extending from a transition-based dependency parsing model. Three neural network based classifiers are designed to resolve the conflicts of transition actions, respectively for shift/reduce (dependency parse tree skeletons), tagging (POS tagging), and labeling (dependency label) disambiguations. Experiments show that our approach significantly outperforms previous methods for joint POS tagging and dependency parsing on three treebanks across eight natural languages.

Figure 1: Part-of-speech tagging and dependency parsing. Given an English sentence “He won the game”, our goal is to predict its corresponding part-of-speech tag sequence “PRP VBD DT NN” and dependency tree \{⟨2, 1, nsubj⟩, ⟨4, 3, det⟩, ⟨2, 4, dobj⟩\}. 
2 Approach

2.1 Problem Statement

As shown in Figure 1 given an English sentence “He won the game”, the corresponding tag sequence is “PRP VBD DT NN”. These tags indicate the part of speech of each word: “He” is a personal pronoun, “won” is a verb in past tense, “game” is a noun.

Figure 1 also shows a dependency tree, which is a collection of dependency arcs. The leftmost arc between the first two words indicates that “won” is a head word. “He” is a modifier, and the syntactic label “nsubj” suggests that “He” is a nominal subject.

More formally, given a natural language sentence \( x = x_1, \ldots, x_N \), we denote its corresponding POS tag sequence as \( t = t_1, \ldots, t_N \), where \( t \in T \) is a POS tag and \( T \) is a set of all possible tags. A dependency tree is denoted by \( d = \{ (h, m, l) | 0 < h \leq N, 0 < m \leq N, l \in L \} \). We use \( (h, m, l) \) to represent a dependency arc, where \( x_h \) is a head word, \( x_m \) is a modifier, and \( l \) is syntactic label. We use \( L \) to denote the set of all possible syntactic labels. The dependency tree in Figure 1 consists of three arcs: \( ⟨ 2, 1, nsubj⟩, ⟨ 2, 4, dobj⟩, and ⟨ 4, 3, det⟩. Therefore, the goal of our work is to generate a tag sequence \( t \) and a dependency tree \( d \) for a given sentence \( x \).

2.2 Transition System

In this work, we leverage a transition-based approach [Nivre, 2008] to joint POS tagging and dependency parsing, which uses classifiers to predict individual actions of shift-reduce algorithms.

We define a **configuration** as a quadruple \( c = (S, B, T, D) \), where

1. \( S \): a stack that is a disjoint sublist of words,
2. \( B \): a buffer that is a sublist of words to be processed,
3. \( T \): a tag sequence that stores the result of POS tagging,
4. \( D \): a dependency arc set that stores the result of dependency parsing.

As shown in Table 1 we define five categories of actions for the transition between configurations:

| Transition | Definition | Condition |
|------------|------------|-----------|
| \( S\) | \( (S, x_n, B, T, D) \) \( \Rightarrow \) \( (S | x_n, B, T, D) \) | \( |B| > 0 \land |T| = N - |B| \land D_{-1,l} \neq \bot \) |
| \( L\) | \( (S | x_m, B, T, D) \) \( \Rightarrow \) \( (S | x_h, B, T, D \cup \{ (h, m, \bot) \}) \) | \( |S| > 1 \land |T| = N - |B| \land D_{-1,l} \neq \bot \) |
| \( R\) | \( (S | x_h, B, T, D) \) \( \Rightarrow \) \( (S | x_h, B, T, D \cup \{ (h, m, \bot) \}) \) | \( |S| > 1 \land |T| = N - |B| \land D_{-1,l} \neq \bot \) |
| \( T\) | \( (S | x_h, B, T, D) \) \( \Rightarrow \) \( (S | x_h, B, T, D \cup \{ (h, m, \bot) \}) \) | \( |T| = |N - |B| - 1 \) |
| \( L\) | \( (S | x_h, B, T, D) \) \( \Rightarrow \) \( (S | x_h, B, T, D \cup \{ (h, m, l) \}) \) | \( D_{-1,l} = \bot \) |

Table 1: Transitions for joint POS tagging and dependency parsing. We use a quadruple \( (S, B, T, D) \) to denote a configuration, which consists of a stack \( S \), a buffer \( B \), a tag sequence \( T \), and a dependency arc set \( D \). We define five categories of actions \( S\): moving a word from the buffer to the stack, \( L\) (generating a left-headed dependency arc), \( R\) (generating a right-headed dependency arc), \( T\) (appending the last word moved into stack as \( t \)), and \( L\) (labeling the last generated arc as \( l \)) for the transitions between configurations. We use \( \bot \) to denote an undefined syntactic label, and \( D_{-1,l} \) to denote the syntactic label of the last generated dependency arc. \( N \) is the length of the input sentence.

2.3 Modeling

Given a sentence \( x \) with \( N \) words, tag sequence \( t \) and dependency tree \( d \) corresponds to a unique sequence of action-configuration pairs \( \{ (c_i, a_i) \}_{i=1}^{4N-2} \) as shown in Table 1.\(^1\) We find that separating tag and label actions (i.e., \( T\) and \( L\) from structural actions (i.e., \( S\), \( L\), and \( R\)) leads to significant improvements over using combined actions.\(^2\)

\(^1\)While it is possible to integrate two actions into one action (e.g., combining \( S\) and \( R\) into \( S\)) [Bohnet and Nivre, 2012].

\(^2\)We follow Chen and Manning [2014] to map a parse to a unique sequence of action-configuration pairs by using the “shortest stack” strategy.
Table 2: The process of joint POS tagging and dependency parsing for the example in Figure 1.

Step | Transition | Stack (S) | Buffer (B) | Tags (T) | Dependencies (D)
--- | --- | --- | --- | --- | ---
0 | SHIFT | He | He | He | PRP
1 | TAGwBD | He | He | won | PRP
2 | SHIFT | He | won | won | PRP
3 | TAGwBD | He | won | won | PRP
4 | LEFT | won | the | game | PRP
5 | LABELnsubj | won | the | the | PRP
6 | SHIFT | won | the | the | PRP
7 | TAGDT | won | the | game | PRP
8 | TAGDT | won | the | game | PRP
9 | SHIFT | won | the | game | PRP
10 | TAGNN | won | the | game | PRP
11 | LEFT | won | game | PRP
12 | LABELdet | won | game | PRP
13 | RIGHT | won | game | PRP
14 | LABELdoobj | won | game | PRP

Note that the number of SHIFT actions is \( N \), LEFT or RIGHT is \( N - 1 \), TAG\(_i\) is \( N \), and LABEL\(_i\) is \( N - 1 \), where SHIFT and TAG\(_i\) have the same number as words, LEFT/RIGHT and LABEL have the same number as dependency arcs.

As a result, the probabilistic model for transition-based joint POS tagging and dependency parsing is defined as

\[
P(t, d | x; \theta) = \prod_{i=1}^{4N-2} P(a_i | c_{i-1}; \theta) \times P(c_i | c_{i-1}, a_i) \tag{1}
\]

Therefore, we only need to focus on the action probability conditioned on the previous configuration.

In our transition system, there are three types of conflicts:

1. **Tag conflict** among all possible POS tags \( \{\text{TAG}_t | t \in T\} \),
2. **Shift/reduce conflict** between SHIFT, LEFT, and RIGHT.
   For example, at step 5 in Table 2 both SHIFT and LEFT can be applied,
3. **Label conflict** among all possible syntactic labels \( \{\text{LABEL}_i | l \in L\} \).

To resolve these conflicts, we develop three corresponding neural network based classifiers. Note that the separation of structural actions from tagging and labeling actions results in three small classifiers with fewer classes (i.e., \(|T|\) classes for the tag classifier, 3 for the shift/reduce classifier, and \(|L|\) for the label classifier) rather than one big classifier with much more classes (i.e., \(|T| + 2|L|\)).

**Basic Features**

We use \( x_n \) to denote the vector representation of the \( n \)-th word \( x_n \). In our experiments, we follow Kiperwasser and Goldberg [2016] to learn \( x_n \) using bidirectional LSTM whose inputs are concatenations of randomly initialized word embeddings with additional pre-trained embeddings as well as character-based representations [dos Santos and Zadrozny, 2014; Ballesteros et al., 2015]. We use \( t_n \) to denote the vector representation of the \( n \)-th POS tag \( t_n \), which can be learned using a unidirectional LSTM based on randomly initialized tag embeddings. Note that the bidirectional LSTM feature representations for words are computed before joint POS tagging and dependency parsing while the unidirectional LSTM feature representations for tags are calculated during the search on the fly.

**Tag Classification**

Resolving the tag conflict is a \(|T|\)-class classification problem. Instead of using conventional feature templates that are highly sparse and inevitably incomplete, we leverage a neural network based classifier. To determine the POS tag of the last word added to the stack, which is represented as \( x_{S_t} \), the input layer consists of the following representations:

1. \( x_{S_0} \): the word representation of the second item in the stack,
2. \( t_{S_0} \): the tag representation of the second item in the stack,
3. \( x_{B_{-2}} \): the word representation of the second last item removed from the buffer,
4. \( t_{B_{-2}} \): the tag representation of the second last item removed from the buffer,
5. \( x_{S_0} \): the word representation of the first item in the stack,
6. \( x_{B_0} \): the word representation of the first item in the buffer.

where, \( x_{B_{-2}}, x_{S_0}, x_{B_0} \) are window-based features that have been widely adopted in previous work [Huang et al., 2015] and \( t_{B_{-2}} \) models the previous tag which has been widely used implicitly by markov assumption in CRF models. Note that \( x_{B_{-2}}, x_{S_0}, x_{B_0} \) are sequential words and \( x_{S_1} \) is not necessarily identical to \( x_{B_{-2}} \) due to the RIGHT action.

We expect that these representations can provide useful contextual information for resolving the tagging ambiguity. Note that the tagging classifier is capable of exploiting syntactic information encoded in \( x_{S_1} \) and \( t_{S_1} \).

As shown in Figure 2(a), the hidden layer is calculated as

\[
h_{tag} = W_{tag}^{(1)}[x_{S_1}; t_{S_1}; x_{B_{-2}}; t_{B_{-2}}; x_{S_0}; x_{B_0}] \tag{2}
\]
Then, the probability for tagging \( x_{S_0} \) as \( t \) is computed at the softmax layer:

\[
P_{\text{tag}}(a|c; \theta) = \text{softmax}
\left( W_{\text{tag}}^{(2)} h_{\text{tag}}^{S_0} \right)
\]

where \( a \in \{ \text{TAG} | t \in \mathcal{T} \} \).

**Shift/Reduce Classification**

Resolving the shift/reduce conflict is a 3-class classification problem. As shown in Figure 2(b), we also use a neural classifier, in which the hidden layer is given by:

\[
h_{\text{parse}} = W_{\text{parse}}^{(1)} [x_{S_2}; t_{S_2}; x_{S_1}; t_{S_1}; x_{S_0}; t_{S_0}; x_{B_0}]
\]

where \( S_2 \) denotes the third item in the stack. Note that the shift/reduce classifier is capable of exploiting lexical information encoded in \( t_{S_2}, t_{S_1}, \) and \( t_{S_0} \).

Therefore, the shift/reduce classification probability is computed as

\[
P_{\text{parse}}(a|c; \theta) = \text{softmax}
\left( W_{\text{parse}}^{(2)} h_{\text{parse}} \right)
\]

where \( a \in \{ \text{SHIFT, LEFT, RIGHT} \} \).

**Label Classification**

Resolving the label conflict is a |\( \mathcal{L} \)|-class classification problem. As shown in Figure 2(c), the corresponding neural classifier takes the word and tag representations of the first two items in the stack as input:

\[
h_{\text{label}} = W_{\text{label}}^{(1)} [x_{S_1}; t_{S_1}; x_{S_0}; t_{S_0}]
\]

Clearly, labeling a dependency arc also depends on tag representations \( t_{S_1} \) and \( t_{S_0} \).

The label classification probability is computed as

\[
P_{\text{label}}(a|c; \theta) = \text{softmax}
\left( W_{\text{label}}^{(2)} h_{\text{label}} \right)
\]

where \( a \in \{ \text{LABEL} | l \in \mathcal{L} \} \).

### 2.4 Training and Parsing

Given a set of training examples \( \{ (x^{(k)}, t^{(k)}, d^{(k)}) \}_{k=1}^{K} \), the training objective is to minimize the cross-entropy loss plus a \( \ell_2 \)-regularization term:

\[
\hat{\theta} = \arg \min_{\theta} \left\{ -\sum_{k=1}^{K} \log P(t^{(k)}, d^{(k)}|x^{(k)}; \theta) + \frac{\lambda}{2} ||\theta||^2 \right\}
\]

In parsing, we follow Chen and Manning [2014] to perform greedy decoding. The most probable tag sequence and dependency tree corresponds to a sequence of action-configuration pairs with the highest probability: \( \{ (\hat{c}_i, \hat{a}_i) \}_{i=1}^{N-2} \), where

\[
\hat{a}_i = \arg \max_a P(a|\hat{c}_{i-1}; \hat{\theta})
\]

and \( \hat{c}_i \) is obtained by applying \( \hat{a}_i \) to \( \hat{c}_{i-1} \).

### 3 Experiments

#### 3.1 Setup

**Datasets and Evaluation**

We evaluate our approach on three datasets: the English Penn Treebank (PTB) with annotated phrase-structure trees of English, the Chinese Penn Treebank (CTB) version 5.1 with annotated phrase-structure trees of Chinese, and the Universal Dependency Treebank (UD) version 1.2 with annotated dependency trees across a number of natural languages.

We use the standard splitting method to divide the PTB dataset into training, development and test sections, and convert the phrase-structure trees into dependency trees by the Stanford dependency converter v3.3.0 [de Marneffe et al., 2006]. For the CTB5.1 dataset, we follow previous work [Hatori et al., 2011; Bohnet and Nivre, 2012] to split the dataset into training, development and test sections, and use the Penn2Malt tool with the head-finding rule of [Zhang and Clark, 2008] to convert the phrase-structure trees into dependency trees. For the UD dataset, we follow Ammar et al. [2016], using the same subset of seven languages including German (de), English (en), Spanish (es), French (fr), Italian (it), Portuguese (pt) and Swedish (sv) and using the same data splitting method.

For POS tagging, we use the standard tagging accuracy (POS) based on words as the major evaluation metric. For dependency parsing, we use two metrics, namely unlabeled attachment score (UAS) and labeled attachment score (LAS), where UAS denotes the ratio of the correctly-headed words with respect to the total words, which considers only the head of a word, and LAS takes into account the dependency label as well, and is employed as the major metric to evaluate dependency parsing.

\[\text{http://universaldependencies.org}\]
Hyper-parameters and Training Details

We tune all hyper-parameters in our models according the development results. Concretely, the dimension sizes of word, tag and character embeddings are 150, 50 and 50, respectively. We use the same pre-trained word embeddings for PTB and CTB5.1 as Chris et al. [2015] and do not use any pre-trained embeddings for UD, and the dimension size of the hidden states in neural classifiers is 300.

We exploit the Adam optimizer [Kingma and Ba, 2015] to update model parameters during training, setting the hyper-parameters $\beta_1$ and $\beta_2$ both to 0.9. Gradient clipping [Pascual et al., 2013] by a max norm 5.0 is used to avoid gradient exploding. To avoid overfitting, we use $\ell_2$-regularization by a parameter $10^{-8}$ as well as the dropout technique [Srivastava et al., 2014] with a drop rate of 0.25. Since the arc-standard algorithm can only handle the projective trees, we apply a projectivization step to the training sets of the UD dataset.

3.2 Main Results

Table 3 shows the final results on the datasets of PTB and CTB5.1, where the tagging accuracy being 100% denotes gold-standard POS tags are employed. We include the results of state-of-the-art previous transition-based parsers as well. In particular, Andor et al. (2016) use beam search in decoding and Bohnet and Nivre (2012) use a different method to produce dependency trees.

Table 4: Final dependency parsing results (LAS) on the UD dataset.

We compare our model with previous work as well. On the one hand, we compare our joint model with previous joint models. As shown in Table 3, our neural joint model shows the highest results for both PTB and CTB5.1, obtaining much higher performances in dependency parsing, which demonstrates the effectiveness of the neural features. On the other hand, we compare our baseline model with state-of-the-art transition-based dependency parsing models. Typically, the PTB results are reported by using auto POS tags and the CTB5.1 results are reported by using gold-standard POS tags, respectively. Our baseline model produces strong enough results for both PTB and CTB5.1.

Table 4 shows the final results on the UD dataset. Joint models also achieve significantly better results in comparison with the pipeline models (p-value below $10^{-5}$), which is similar to our finding on CTB5.1. Besides, our joint model achieves the best-reported results among the transition-based models, even by using a greedy manner for decoding, which can be attributed to the effective exploration of the interaction between the tagging and parsing in our joint model, while no previous work has studied it under the neural setting to our knowledge. The work of Zhang and Weiss [2016] resembles our work most, which improve a feed-forward dependency parser by using POS tags in a pipeline way by stack-propagation. While our joint model benefits from the use of LSTM, and in addition, we find that directly using the resulting tags rather than the penultimate hidden representations of a tag classifier leads to better results.
Bohnet and Nivre, 2012]. They introduce transition systems that can perform POS tagging and dependency parsing in a with feature templates [Li et al., 2011; Hatoni et al., 2011].

### 3.3 Discussion

To investigate the effect of POS tagging on dependency parsing, we conduct analysis on the CTB5.1 dataset to illustrate the effectiveness of the joint model. Here we examine in detail to see the benefits from the interaction between tagging and parsing in our joint model. First, we can remove the tag representations from parsing in Eq. (4) and Eq. (5):

\[
\hat{h}_{\text{parse}} = W^{(1)}_{\text{parse}} [x_{S_i}; x_{S_i}; x_{R_0}]
\]

\[
\hat{h}_{\text{label}} = W^{(1)}_{\text{label}} [x_{S_i}; x_{S_0}]
\]

Similarly, we can also remove the syntactic information from tagging in Eq. (2) to investigate the effect of dependency parsing on POS tagging:

\[
\hat{h}_{\text{tag}} = W^{(1)}_{\text{tag}} [x_{B_{-2}}; x_{B_{-2}}; x_{S_0}; x_{R_0}]
\]

Table 5 gives the tagging and parsing results on the CTB 5.1 development set. We observe that disabling the interactions between tagging and parsing significantly deteriorates both tagging and parsing quality.

An interesting finding is that providing lexical information to parsing (“tag \(\rightarrow\) parse”) leads to more benefits than providing syntactic information to tagging (“tag \(\leftarrow\) parse”). This is because tagging ambiguity is mostly local while dependency parsing heavily depends on POS tags to predict syntactic structures.

Note that enabling “tag \(\rightarrow\) parse” only also improves the tagging accuracy itself. One possible reason is that tagging and parsing is still connected via the sharing of word embeddings and bidirectional LSTM hidden states although the connection at hidden layer in classifiers is explicitly disabled.

### 5 Conclusion

We have presented an approach to joint part-of-speech tagging and dependency parsing using transition-based neural networks. Based on a five-action transition system, we develop three classifiers to resolve structural, tagging, and labeling conflicts. As our approach allows lexicality and syntactic structures to interact with each other in the joint search process, it improves over previous work on joint POS tagging and dependency parsing on three treebanks across a variety of natural languages. Our code is released at [http://github.com/lineryang/joint-parser](http://github.com/lineryang/joint-parser).

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### Table 5: Interaction between POS tagging and dependency parsing

| Interaction | POS | UAS | LAS |
|-------------|-----|-----|-----|
| tag \(\rightarrow\) parse | ×   | 95.19 | 83.38 | 80.66 |
| tag \(\leftarrow\) parse | √   | 95.25 | 83.56 | 80.82 |
| tag \(\rightarrow\) parse | ×   | 95.50 | 84.10 | 81.59 |
| tag \(\leftarrow\) parse | √   | 95.63 | 84.20 | 81.76 |

Note that enabling "tag \(\rightarrow\) parse" only also improves the tagging accuracy itself. One possible reason is that tagging and parsing is still connected via the sharing of word embeddings and bidirectional LSTM hidden states although the connection at hidden layer in classifiers is explicitly disabled.

Our transition system differs from previous work in the separation of structural, tagging, and labeling actions. This results in three small classifiers with fewer classes (i.e., \(|T|\) classes for the tag classifier, 3 for the shift/reduce classifier, and \(|C|\) for the label classifier) rather than one big classifier with much more classes (i.e., \(|T| + 2|C|\)).

More importantly, we use continuous representations instead of discrete indicator features to build the classifiers. As indicated by Chen and Manning [2014], lexicalized indicator features crucial for improving parsing accuracy are highly sparse and often incomplete. Alternatively, we resort to neural networks to learn representations from data to circumvent the sparsity and incompleteness problems. Another benefit of using neural networks is that there is no need to compose individual features to obtain more complex features like conventional discriminative dependency parsing [Dyer et al., 2015].

### 4.2 Neural POS Tagging and Dependency Parsing

Our work is also inspired by recent advances in applying neural networks to POS tagging [Huang et al., 2015] and dependency parsing [Chen and Manning, 2014; Dyer et al., 2015; Ballesteros et al., 2015; Alberti et al., 2015; Ammar et al., 2015; Kiperwasser and Goldberg, 2016; Andor et al., 2016; Wang and Chang, 2016; Cheng et al., 2016; Dozat and Manning, 2017].

Among them, our work bears the most resemblance to [Zhang and Weiss, 2016], which propose stack-propagation to integrate a tagging model into a neural parser. They propose a stacked pipeline of models and utilize POS tags as a regularizer of learned representations. While Zhang and Weiss [2016] use the hidden layer of the tagger network as the input for the parser, we are interested in enabling tagging and parsing to benefit each other in a joint search space. As a result, the tagger is able to resolve long-distance tagging ambiguity by exploiting syntactic information. Meanwhile, the error propagation problem the parser faces can be alleviated due to the cascaded error reduction by joint modeling.
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