Learning to Search for Dependencies

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Abstract

We create a transition-based dependency parser using a general purpose learning to search system. The result is a fast and accurate parser for many languages. Compared to other transition-based dependency parsing approaches, our parser provides similar statistical and computational performance with best-known approaches while avoiding various downsides including randomization, extra feature requirements, and custom learning algorithms. We show that it is possible to implement a dependency parser with an open-source learning to search library in about 300 lines of C++ code, while existing systems often require several thousands of lines.

1 Introduction

Dependency parsing is a well-known problem with a long history of development resulting in many solutions (McDonald et al., 2005; Nivre, 2003; Koo et al., 2008; Goldberg and Elhadad, 2010; Goldberg et al., 2014). Virtually all of these solutions use various problem-specific customizations of machine learning algorithms or problem-specific customizations of feature sets. In this paper, we aim to answer the following question: Is it possible to use a general purpose learning algorithm with only basic features to effectively solve dependency parsing?

To be general purpose, the system must solve a wide array of other problems as well. To approach this goal, we investigated using a learning to search system (L2S) (Daumé III et al., 2014) which has been used to solve about a half-dozen other structured prediction problems. The learning to search system in turn relies on a machine learning subsystem which is in broad use by 1000’s of people.

<table>
<thead>
<tr>
<th>Dependency Parser</th>
<th>Number of lines</th>
</tr>
</thead>
<tbody>
<tr>
<td>L2S (ours)</td>
<td>∼300</td>
</tr>
<tr>
<td>Stanford</td>
<td>∼3K</td>
</tr>
<tr>
<td>RedShift</td>
<td>∼2K</td>
</tr>
<tr>
<td>(Goldberg and Nivre, 2013)</td>
<td>∼4K</td>
</tr>
<tr>
<td>Malt Parser</td>
<td>∼10K</td>
</tr>
</tbody>
</table>

Table 1: Number of lines of dependency parser implementations.

To use a learning to search approach a search space must be defined. A natural choice for a search space is given by the sequence of actions of a transition-based parser. Several authors have investigated transition-based parser approaches (Goldberg and Nivre, 2013; Zhang and Nivre, 2011; Chen and Manning, 2014; Kuhlmann et al., 2011) achieving success with custom learning algorithms or custom features. Here, we show this is possible with standard learning algorithms. Aside from the overall transition-based dependency parsing structure, the L2S parser uses a dynamic oracle (Goldberg and Nivre, 2013) and a single-hidden-layer neural network “for free” (enabled by a simple flag), as opposed to a system built from scratch to use neural networks (Chen and Manning, 2014).

The primary advantage of this approach is a combination of correctness and simplicity. The simplicity is evidenced several ways:

1. It requires only ∼300 lines of C++ code when implementing based on an open-source learning to search library\textsuperscript{1}. Table 1 shows the number of lines of other popular dependency parsing systems.

2. We do not randomize 5 times and take the best result as in (Goldberg and Nivre, 2013).

\textsuperscript{1}Available at: https://github.com/JohnLangford/vowpal_wabbit
3. The implementation is future-proofed: future improvements in underlying machine learning algorithms and learning to search framework may yield a better parser.

Correctness is a more subtle issue. Regret analysis of learning to search (Daumé III et al., 2009; Ross et al., 2011; Ross and Bagnell, 2014; Chang et al., 2015) suggests how to settle various details:

1. Use a cost sensitive learning algorithm instead of a multiclass learning algorithm.
2. Use rollouts with the learned policy.
3. Use rollouts with either a good reference policy or a mixture of reference and learned policy.

Many of these details are correctly hand-crafted in individual implementations, but it is also common to neglect one of these details, with any neglect resulting in an inconsistent approach. Empirically an inconsistent approach has a lower ceiling performance. Having a system which gets these details correct every time is a large part of the value of a learning to search system.

Experiments evaluated on standard English Penn Treebank and 9 other languages from CoNLL-X show that our parser is competitive with recent published results (an average labeled accuracy of 81.70 over 10 languages, versus 80.33 and 75.34 for state of the art parsers published last year). We achieve this with this much simpler implementation and with the strong theoretical guarantees inherited from learning to search.

## 2 Learning to Search

Learning to search is a family of approaches for solving structured prediction tasks. This family includes a number of specific algorithms including the incremental structured perceptron (Collins and Roark, 2004; Huang et al., 2012), SeARN (Daumé III et al., 2009), DAGGER (Ross et al., 2011),

Algorithm 1 RunTagger(words)

```
1: output ← []
2: for n = 1 to len(words) do
3: ref ← words[n], true_label
4: output[n] ← PREDICT(words[i], ref, output[n-1])
5: end for
6: loss(# parent[n] ≠ parent[n], true_label)
7: return output
```

AGGREGATE (Ross and Bagnell, 2014), and others (Daumé III and Marcu, 2005; Xu and Fern, 2007; Xu et al., 2007; Ratliff et al., 2007; Syed and Schapire, 2011; Doppa et al., 2012; Doppa et al., 2014). Learning to search approaches solve structured prediction problems by (1) decomposing the production of the structured output in terms of an explicit search space (states, actions, etc.); and (2) learning hypotheses that control a policy that takes actions in this search space.

In this work we build on recent theoretical and implementational advances in learning to search that make development of novel structured prediction frameworks easy and efficient using “imperative learning to search” (Daumé III et al., 2014). In this framework, an application developer needs to write (a) a “decoder” for the target structured prediction task (e.g., dependency parsing), (b) an annotation in the decoder that computes losses on the training data, and (c) a reference policy on the training data that returns at any prediction point a suggestion as to a good action to take at that state.

Algorithm 1 shows the code one must write for a part of speech tagger (or generic sequence labeler) under Hamming loss. The only annotation in this code aside from the calls to the library function PREDICT are the computation of an reference (an oracle reference is trivial under Hamming loss) and the computation of the total sequence loss at the end of the function. Note that in this example, the prediction of the tag for the $n$th word depends explicitly on the predictions of all previous words!

The machine learning question that arises is how to learn a good PREDICT function given just this information. The “imperative learning to search” answer (Daumé III et al., 2014) is essentially to run the RUNTAGGER function many times, “trying out” different versions of PREDICT in order to learn one that yields low LOSS. The

2Inconsistency is a subtle issue that is often not dealt with properly even in machine learning. Inconsistency is important when the truth is noisy. A simple illustrative example of inconsistency occurs when reducing 3-class classification to binary classification via a one-against-all approach (1 vs \{2, 3\}, 2 vs \{1, 3\}, and 3 vs \{2, 1\}). When the class label is inherently uncertain, with probability 0.4 for label 1 and 0.3 for label 2 and 3, the learned binary classifier prefers \{2, 3\}, \{1, 3\}, \{2, 1\} since in each case the probability of the pair of labels exceeds the probability of the single missing label. However, these predictions give no preference for label 1 which is the most likely class.

3Some papers in the past make an implicit or explicit assumption that this reference policy is an oracle policy: for every state, it always chooses the best action (assuming it gets to make all future decisions as well).
challenge is how to do this efficiently. The general strategy is, for some number of epochs, and for each example \((x, y)\) in the training data, to do the following:

1. Execute \textsc{RUNTAGGER} on \(x\) with some \texttt{rollin policy} to obtain a search trajectory (sequence of action \(a\)) and loss \(\ell_0\)
2. Many times:
   a. Choose some time step \(t \leq |a|\)
   b. Choose an alternative action \(a'_t \neq a_t\)
   c. Execute \textsc{RUNTAGGER} on \(x\) with \texttt{predict} return \(a_{t-1}\) initially, then \(a'_t\), then acting according to a \texttt{rollout policy} to obtain a new loss \(\ell_{t,a'_t}\)
   d. Compare the overall losses \(\ell_0\) and \(\ell_{t,a'_t}\) to construct a classification/regression example that demonstrates how much better or worse \(a'_t\) is than \(a_t\) in this context
3. Update the learned policy

Figure 1 shows a schematic of the search space implicitly defined by an imperative program. By executing this program three times (in this example), we are able to explore three different trajectories and compute their losses. These trajectories are defined by the \texttt{rollin policy} (what determines the initial trajectory), the position of one-step deviations (here, state \(R\)), and the \texttt{rollout policy} (which completes the trajectory after a deviation).

By varying the \texttt{rollin policy}, the \texttt{rollout policy} and the manner in which classification/regression examples are created, this general framework can mimic algorithms like \textsc{SEARN}, \textsc{DAGGER} and \textsc{AGGREGATE}. For instance, \textsc{DAGGER} uses \texttt{rollin}=learned policy\(^4\) and \texttt{rollout}=reference, while \textsc{SEARN} uses \texttt{rollin}=\texttt{rollout}=stochastic mixture of learned and reference policies.

3 Dependency Parsing by Learning to Search

Learning to search provides a natural framework for implementing a transition-based dependency parser. A transition-based dependency parser takes a sequence of actions and parses a sentence from left to right by maintaining a \textit{stack} \(S\), a \textit{buffer} \(B\), and a set of \textit{dependency arcs} \(A\). The stack maintains partial parses, the buffer stores the words to be parsed, and \(A\) keeps the arcs that have been generated so far. The configuration of the parser at each stage can be defined by a triple \((S, B, A)\).

For the ease of notation, we use \(w_p\) to represent the leftmost word in the buffer and use \(s_1\) and \(s_2\) to denote the top and the second top words in the stack. A dependency arc \((w_h, w_m)\) is a directed edge that indicates word \(w_h\) is the parent of word \(w_m\). When the parser terminates, the arcs in \(A\) form a projective dependency tree. We assume that each word only has one parent in the derived dependency parse tree, and use \(A[w_m]\) to denote the parent of word \(w_m\). For labeled dependency parsing, we further assign a tag to each arc representing the dependency type between the head and the modifier. For simplicity, we assume an unlabeled parser in the following description. The extension from an unlabeled parser to a labeled parser is straightforward, and is discussed at the end of this section.

We consider an arc-hybrid transition system (Kuhlmann et al., 2011)\(^5\). In the initial con-

\(^4\)Technically, \textsc{DAGGER} rolls in with a mixture which is almost always instantiated to be “reference” for the first epoch and “learned” for subsequent epochs.

\(^5\)The learning to search framework is also suitable for other transition-based dependency parsing systems, such as arc-eager (Nivre, 2003) or arc-standard (Nivre, 2004) transition systems.

Flying planes can be dangerous

Algorithm 2: TRANS($S$, $B$, $A$, action)

1. Let $w_p$ be the leftmost element in $B$
2. if action = SHIFT then
   3. $S$.push($w_p$)
   4. remove $w_p$ from $B$
5. else if action = REDUCE-LEFT then
   6. $top$ ← $S$.pop()
   7. $A$ ← $A$∪($w_p$, $top$)
8. else if action = REDUCE-RIGHT then
   9. $top$ ← $S$.pop()
10. $A$ ← $A$∪($S$.top(), $top$)
11. end if
12. return $S$, $B$, $A$

Algorithm 3: RUNPARSER(sentence)

1. stack $S$ ← \{Root\}
2. buffer $B$ ← \{words in sentence\}
3. arcs $A$ ← $\emptyset$
4. while $B \neq \emptyset$ or $|S| > 1$ do
5. ValidActs ← GETVALIDACTIONS($S$, $B$)
6. features ← GETFEAT($S$, $B$, $A$)
7. ref ← GETGOLDACTION($S$, $B$)
8. action ← PREDICT(features, ref, ValidActs)
9. $S$, $B$, $A$ ← TRANS($S$, $B$, $A$, action)
10. end while
11. LOSS($A[w]$) ≠ $A^*[w]$, $\forall w \in$ sentence)
12. return output

We can define a search space for dependency parser such that each state represents one configuration during the parsing. The start state is associated with the initial configuration, and the end states are associated with the configurations that $|B| = 0$ and $S = \{\text{Root}\}$. The loss of each end state is defined by the distance between the derived parse tree and the gold parse tree. The above transition actions define how to move from one search state to the other. In the following, we describe our implementation details.

Implementation As mentioned in Section 2, to implement a parser using the learning to search framework, we need to provide a decoder, a loss function and reference policy. Thanks to recent work (Goldberg and Nivre, 2013), we know how to compute a “dynamic oracle” reference policy that is optimal. The loss can be measured by how many parents are different between the derived parse tree and the gold annotated parse tree. Algorithm 3 shows the pseudo-code of a decoder for
a unlabeled dependency parser. We discuss each subcomponent below.

- **GETVALIDACTION** returns a set of valid actions that can be taken based on the current configuration.
- **GETFEAT** extracts features based on the current configuration. The features depend on the top few words in the stack and leftmost few words in the buffer as well as their associated part-of-speech (POS) tags. We list our feature templates in Table 3. All features are generated dynamically because configuration changes during parsing.
- **GETGOLDACTION** implements the dynamic oracle described in (Goldberg and Nivre, 2013). The dynamic oracle returns the optimal action at any state that leads to the reachable end state with the minimal loss.
- **PREDICT** is a library call implemented in the learning to search system. Given training samples, the learning to search system can learn the policy automatically. Therefore, in the test phase, this function returns the predicted action leading to an end state with small structured loss.
- **TRANS** function implements the hybrid-arc transition system. Based on the predicted action and labels, it updates the parser’s configuration, and move the agent to the next search state.
- **LOSS function** is used to measure the distance between the predicted output and the gold annotation. Here, we simply used the number of words for which the parent is wrong as the loss. The LOSS has no effect in the test phase.

The above decoder implements an unlabeled parser. To build a labeled parser, when the transition action is REDUCE-LEFT or REDUCE-RIGHT, we call the PREDICT function again to predict the dependency type of the arc. The loss in the labeled dependency parser can be measured by \( \sum_{w_i} \text{loss}(w_i) \), where

\[
\text{loss}(w_i) = \begin{cases} 
2 & A[w_i] \neq A^*[w_i] \\
1 & A[w_i] = A^*[w_i], L[w_i] \neq L^*[w_i] \\
0 & \text{Otherwise}.
\end{cases}
\]

(1)

\( A[w_i] \) and \( A^*[w_i] \) are the parent of \( w_i \) in the derived parse tree and gold parse tree, respectively, \( L[w_i] \) is the label assign to the arc \( (A[w_i], w_i) \).

We observe that this simple loss function performs well empirically.

We implemented our parser based on an open-source library supporting learning to search. The implementation requires about 300 lines of C++ code. Table 2 shows the number of code lines for each function. The reduction of implementation

<table>
<thead>
<tr>
<th>Function</th>
<th>Number of lines</th>
</tr>
</thead>
<tbody>
<tr>
<td>Setup</td>
<td>70</td>
</tr>
<tr>
<td>GETVALIDACTION</td>
<td>17</td>
</tr>
<tr>
<td>GETFEAT</td>
<td>85</td>
</tr>
<tr>
<td>GETGOLDACTION</td>
<td>41</td>
</tr>
<tr>
<td>TRANS</td>
<td>31</td>
</tr>
<tr>
<td>RUNPARSER</td>
<td>70</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>314</strong></td>
</tr>
</tbody>
</table>

Table 2: Number of code lines of our dependency parser implementation. Proper comments and spacing are included. The “Setup” contains class constructor, destructor, and handlers for the learning to search framework.

<table>
<thead>
<tr>
<th>Function</th>
<th>Number of lines</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unigram Features</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( s_1, s_2, s_3, b_1, b_2, b_3, L_1(s_1), L_2(s_1), R_1(s_1), R_1(s_2), L_1(b_1), L_2(b_1), L_1(s_2) )</td>
</tr>
<tr>
<td>Bigram Features</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( s_1s_1, s_2s_2, s_3s_3, b_1b_1, b_2b_2, b_3b_3, s_1b_1, s_1s_2, b_1b_2 )</td>
</tr>
<tr>
<td>Trigram Features</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( s_1s_2s_3, s_1b_1b_2, s_2s_2b_3, s_3b_1b_2, b_1b_2b_3, s_1R_1(s_1)R_1(s_2), s_1L_2(s_1)L_2(b_1), b_1L_1(b_1)L_2(b_1), s_1s_2L_1(b_1), s_1b_1L_1(s_1), s_1b_1L_1(s_2), s_1b_1L_1(b_1) )</td>
</tr>
</tbody>
</table>

Table 3: Features used in our dependency parsing system. \( s_i \) represents the \( i \)-th top element in the stack \( S \). \( b_i \) is the \( i \)-th leftmost word in the buffer \( B \). \( L_i(w) \) and \( R_i(w) \) are the \( i \)-th leftmost child and rightmost child of the word \( w \). For each feature template, we includes the surface string and the associated part-of-speech (POS) tag as features. For \( R_i(w) \) and \( L_i(w) \), we also include arc labels as features. A feature hashing technique (Weinberger et al., 2009) is employed to provide a fast feature lookup.
effort comes from two-folds. First, in the learning to search framework, there is no need to implement a learning algorithm. Once the decoding function is defined, the system is able to learn the best “PREDICT” function from training data. Second, L2S provides a unified framework, which allows the library to serve common functions for ease of implementation. For example, quadratic and cubic feature generating functions and a feature hashing mechanism are provided by the library. The unified framework also allows a user to experiment with different base learners and hyperparameters using command line arguments without modifying the code.

**Base Learner** As mentioned in Section 2, the learning to search framework reduces structured prediction to cost-sensitive multi-class classification, which can be further reduced to regression. This reduction framework allows us to employ well-studied binary and multi-class classification methods as the base learner. We analyze the value of using more powerful base learners in the experiment section.

### 4 Experimental Results

While most work compares with MaltParser or MSTParser, which are indeed weak baselines, we compare with two recent strong baselines: the greedy transition-based parser with dynamic oracle (Goldberg and Nivre, 2013) and the Stanford neural network parser (Chen and Manning, 2014). We evaluate on a wide range of different languages, and show that our parser achieves comparable or better results on all languages, with significantly less engineering.

#### 4.1 Datasets

We conduct experiments on the English Penn Treebank (PTB) (Marcus et al., 1993) and the CoNLL-X (Buchholz and Marsi, 2006) datasets for 9 other languages, including Arabic, Bulgarian, Chinese, Danish, Dutch, Japanese, Portuguese, Slovene and Swedish. For PTB, we convert the constituency trees to dependencies by the head rules of Yamada and Matsumoto (2006). We follow the standard split: sections 2 to 21 for training, section 22 for development and section 23 for testing. The POS tags in the evaluation data is assigned by the Stanford POS tagger (Toutanova et al., 2003), which has an accuracy of 97.2% on the PTB test set. For CoNLL-X, we use the given train/test splits and reserve the last 10% of training data for development if needed. The gold POS tags given in the CoNLL-X datasets are used.

#### 4.2 Setup and Parameters

For L2S, the rollin policy is a mixture of the current (learned) policy and the reference (dynamic oracle) policy. The probability of executing the reference policy decreases over each round. Specifically, we set it to be $1 - (1 - \alpha)^t$, where $t$ is the number of rounds and $\alpha$ is set to $10^{-5}$ in all experiments. It has been shown (Ross and Bagnell, 2014; Chang et al., 2015) that when the reference policy is optimal, it is preferable to roll out with the reference. Therefore, we roll out with the dynamic oracle (Goldberg and Nivre, 2013).

Our base learner is a simple neural network with one hidden layer. The hidden layer size is 5 and we do not use word or POS tag embeddings. We find the Follow-the-Regularized-Leader-Proximal (FTRL) online learning algorithm particularly effective with learning the neural network and simply use default hyperparameters.

We compare with the recent transition-based parser with dynamic oracles (DYNA) (Goldberg and Nivre, 2013), and the Stanford neural network parser (SNN) (Chen and Manning, 2014). Settings of the three parsers are shown in Table 5.

For DYNA, we use the software provided by the authors online. Our initial experiments show that its performance is the best using the arc hybrid system with exploration parameters $k = 1$, $p = 1$, thus we use this setting for all experiments. The best model evaluated on the development set among 5 runs with different random seeds are chosen for testing.

For SNN, we use the latest Stanford parser. Since all other parsers do not use external resources, we do not provide pretrained word embeddings and initialize randomly. We use the same

<table>
<thead>
<tr>
<th>Parser</th>
<th>Transition</th>
<th>Base learner</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>L2S</td>
<td>arc-hybrid</td>
<td>NN</td>
<td>Dynamic</td>
</tr>
<tr>
<td>DYNA</td>
<td>arc-hybrid</td>
<td>perceptron</td>
<td>Dynamic</td>
</tr>
<tr>
<td>SNN</td>
<td>arc-standard</td>
<td>NN</td>
<td>Static</td>
</tr>
</tbody>
</table>

Table 5: Parser settings.

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6 Available at [https://bitbucket.org/yoavgo/tacl2013dynamicoracles](https://bitbucket.org/yoavgo/tacl2013dynamicoracles)
Table 4: UAS and LAS on PTB and CoNLL-X. The average score over all languages is shown in the last column. The best scores for each language is bolded.

<table>
<thead>
<tr>
<th>Parser</th>
<th>AR</th>
<th>BU</th>
<th>CH</th>
<th>DA</th>
<th>Du</th>
<th>En</th>
<th>Ja</th>
<th>Po</th>
<th>Sl</th>
<th>Sw</th>
<th>Avg</th>
</tr>
</thead>
<tbody>
<tr>
<td>L2S</td>
<td>77.59</td>
<td>90.64</td>
<td>90.46</td>
<td>88.03</td>
<td>78.06</td>
<td>92.30</td>
<td>90.89</td>
<td>89.77</td>
<td>81.28</td>
<td>89.12</td>
<td>86.81</td>
</tr>
<tr>
<td>DYNA</td>
<td>77.89</td>
<td>89.54</td>
<td>89.41</td>
<td>87.37</td>
<td>74.63</td>
<td>91.84</td>
<td>92.72</td>
<td>85.82</td>
<td>77.14</td>
<td>87.85</td>
<td>85.42</td>
</tr>
<tr>
<td>SNN</td>
<td>67.37</td>
<td>88.05</td>
<td>87.31</td>
<td>82.98</td>
<td>75.34</td>
<td>90.20</td>
<td>89.45</td>
<td>83.19</td>
<td>63.60</td>
<td>85.70</td>
<td>81.32</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parser</th>
<th>L2S</th>
<th>66.44</th>
<th>85.07</th>
<th>86.43</th>
<th>81.36</th>
<th>73.55</th>
<th>91.09</th>
<th>89.53</th>
<th>84.68</th>
<th>72.48</th>
<th>82.81</th>
<th>81.34</th>
</tr>
</thead>
<tbody>
<tr>
<td>DYNA</td>
<td>66.33</td>
<td>84.73</td>
<td>85.14</td>
<td>82.30</td>
<td>70.26</td>
<td>90.81</td>
<td>90.91</td>
<td>82.00</td>
<td>68.65</td>
<td>82.21</td>
<td>80.33</td>
<td></td>
</tr>
<tr>
<td>SNN</td>
<td>51.72</td>
<td>84.01</td>
<td>82.72</td>
<td>77.44</td>
<td>71.96</td>
<td>89.10</td>
<td>87.37</td>
<td>77.88</td>
<td>51.08</td>
<td>80.09</td>
<td>75.34</td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Performance of different base learning algorithms with the L2S parser on PTB corpus.

<table>
<thead>
<tr>
<th>Base Learner</th>
<th>Dev</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UAS</td>
<td>LAS</td>
</tr>
<tr>
<td>SGD</td>
<td>89.34</td>
<td>88.03</td>
</tr>
<tr>
<td>Default</td>
<td>90.91</td>
<td>89.46</td>
</tr>
<tr>
<td>NN</td>
<td>92.02</td>
<td>90.78</td>
</tr>
<tr>
<td>NN+FTRL</td>
<td>92.27</td>
<td>91.04</td>
</tr>
</tbody>
</table>

Table 7: The contribution of Bi-gram and Tri-gram features. Results are evaluated on the dev and the test set of PTB.

<table>
<thead>
<tr>
<th>Base Learner</th>
<th>Dev</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UAS</td>
<td>LAS</td>
</tr>
<tr>
<td>Uni-gram</td>
<td>80.41</td>
<td>78.01</td>
</tr>
<tr>
<td>Uni- + Bi-gram</td>
<td>90.73</td>
<td>89.46</td>
</tr>
<tr>
<td>All features</td>
<td>92.27</td>
<td>91.04</td>
</tr>
</tbody>
</table>

The Value of Strong Base Learners

As mentioned in Section 3, a key advantage of L2S framework is that we can leverage from well studied binary and multi-class calcification methods in the literature. In this section, we show the empirical evidence for this merit.

We compare the performance of our parser when training with the following base learners

- **SGD**: a learner with SGD update rules
- **Default**: the default base classifier. This is an improved SGD-style update rule using an adaptive metric (Duchi et al., 2011; McMahan and Streeter, 2010), importance invariant updates (Karampatziakis and Langford, 2011), and normalized updates (Ross et al., 2013).
- **NN**: a single-hidden-layer neural network with 5 hidden nodes.

Parameter values as suggested in (Chen and Manning, 2014), which are also the default settings of the software. The best model over 20000 iterations evaluated on the development set is used for testing.\(^8\)

In addition, we compare with the RedShift\(^9\) parser on PTB. For fair comparison, we only use its basic features (excluding features based on the Brown cluster). We use the default parameters, which runs a beam search with width 8. In our experiments, the RedShift parser has UAS 92.10 and LAS 90.83 on the PTB test set.

4.3 Results

We report unlabeled attachment scores (UAS) and labeled attachment scores (LAS) in Table 4.\(^10\) Punctuation is excluded in all evaluations. Our parser achieves up to 4% improvement on both UAS and LAS. Compared with DYNA, our parser has the same transition system and oracle but more powerful base learners to choose from. Compared with SNN, we use much fewer hidden units and parameters to tune.

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\(^8\)Enabled by `-saveIntermediate`.

\(^9\)Available at https://github.com/syllog1sm/redshift

\(^10\) We notice that the Stanford neural network parser does particularly bad on Arabic, Portuguese and Slovene. One reason is that these languages do not have a "ROOT" label in the dataset, and this is currently not handled well by the software.
• NN + FTRL: a neural network learner with follow-the-regularized-leader regularization. This is the base learner we used in our parsing system.

Table 6 shows the performance of our parser on PTB data with different base classifiers. Results show that using a strong base learner can improve the performance by around 3%.

Finally, Figure 7 shows the performance of different feature templates. Using a comprehensive set of features leads to a better dependency parser.

6 Related Work

Training a transition-based dependency parser can be viewed as an imitation learning problem. However, most early works focus on decoding or feature engineering instead of the core learning algorithm. For a long time, averaged perceptron is the default learner for dependency parsing. Goldberg and Nivre (2013) first proposed dynamic oracles under the framework of imitation learning. Their approach is essentially a special case of our algorithm: the base learner is a multi-class perceptron, and no rollout is executed to assign cost to actions. In this work, we combine dynamic oracles into learning and explore the search space in a more principled way by learning to search: by cost-sensitive classification, we evaluate the end result of each non-optimal action instead of treating them as equally bad.

There are a number of works that use the L2S approach to solve various other structured prediction problems, for example, sequence labeling (Doppa et al., 2014), coreference resolution (Ma et al., 2014), graph-based dependency parsing (He et al., 2013). However, these works can be considered as a special setting under our unified learning framework, e.g., with a custom action set or different rollout methods.

To our knowledge, this is the first work that develops a general programming interface for dependency parsing, or more broadly, for structured prediction. Our system bears some resemblance to probabilistic programming language (e.g., (McCullum et al., 2009; Gordon et al., 2014)), however, instead of relying on a new programming language, ours is implemented in C++ and Python, thus is easily accessible.

7 Conclusion and Discussion

We have described a simple transition-based dependency parser based on the learning to search framework. We show that it is now much easier to implement a high-performance dependency parser. Furthermore, we provide a wide range of advanced optimization methods to choose from during training. Experimental results show that we consistently achieve better performance across 10 languages. An interesting direction for future work is to extend the current system beyond greedy search. In addition, there is a large room for speeding up training time by smartly choosing where to rollout.

References


