Training with Exploration Improves a Greedy Stack LSTM Parser

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Abstract

We adapt the greedy stack LSTM dependency parser of Dyer et al. (2015) to support a training-with-exploration procedure using dynamic oracles (Goldberg and Nivre, 2013) instead of assuming an error-free action history. This form of training, which accounts for model predictions at training time, improves parsing accuracies. We discuss some modifications needed in order to get training with exploration to work well for a probabilistic neural network dependency parser.

1 Introduction

Natural language parsing can be formulated as a series of decisions that read words in sequence and incrementally combine them to form syntactic structures; this formalization is known as transition-based parsing, and is often coupled with a greedy search procedure (Yamada and Matsumoto, 2003; Nivre, 2003; Nivre, 2004; Nivre, 2008). The literature on transition-based parsing is vast, but all works share in common a classification component that takes into account features of the current parser state and predicts the next action to take conditioned on the state. The state is of unbounded size.

Dyer et al. (2015) presented a parser in which the parser’s unbounded state is embedded in a fixed-dimensional continuous space using recurrent neural networks. Coupled with a recursive tree composition function, the feature representation is able to capture information from the entirety of the state, without resorting to locality assumptions that were common in most other transition-based parsers. The use of a novel stack LSTM data structure allows the parser to maintain a constant time per-state update, and retain an overall linear parsing time.

The Dyer et al. parser was trained to maximize the likelihood of gold-standard transition sequences, given words. At test time, the parser makes greedy decisions according to the learned model. Although this setup obtains very good performance, the training and testing conditions are mismatched in the following way: at training time the historical context of an action is always derived from the gold standard (i.e., perfectly correct past actions), but at test time, it will be a model prediction.

In this work, we adapt the training criterion so as to explore parser states drawn not only from the training data, but also from the model as it is being learned. To do so, we use the method of Goldberg and Nivre (2012; 2013) to dynamically chose an optimal (relative to the final attachment accuracy) action given an imperfect history. By interpolating between algorithm states sampled from the model and those sampled from the training data, more robust predictions at test time can be made. We show that the technique can be used to improve the strong parser of Dyer et al.

2 Parsing Model and Parameter Learning

Our departure point is the parsing model described by Dyer et al. (2015). We do not describe the model in detail, and refer the reader to the original work. At each stage $t$ of the parsing process, the parser state is
encoded into a vector \( \mathbf{p}_t \), which is used to compute the probability of the parser action at time \( t \) as:

\[
p(z_t \mid \mathbf{p}_t) = \frac{\exp \left( \mathbf{g}_z^\top \mathbf{p}_t + q_z \right)}{\sum_{z' \in \mathcal{A}(S,B)} \exp \left( \mathbf{g}_{z'}^\top \mathbf{p}_t + q_{z'} \right)}, \tag{1}
\]

where \( \mathbf{g}_z \) is a column vector representing the (output) embedding of the parser action \( z \), and \( q_z \) is a bias term for action \( z \). The set \( \mathcal{A}(S,B) \) represents the valid transition actions that may be taken in the current state. Since \( \mathbf{p}_t \) encodes information about all previous decisions made by the parser, the chain rule gives the probability of any valid sequence of parse transitions \( z \) conditional on the input:

\[
p(z \mid \mathbf{w}) = \prod_{t=1}^{|z|} p(z_t \mid \mathbf{p}_t). \tag{2}
\]

The parser is trained to maximize the conditional probability of taking a “correct” action at each parsing state. The definition of what constitutes a “correct” action is the major difference between a static oracle as used by Dyer et al. (2015) and the dynamic oracle explored here.

Regardless of the oracle, our training implementation constructs a computation graph (nodes that represent values, linked by directed edges from each function’s inputs to its outputs) for the negative log probability for the oracle transition sequence as a function of the current model parameters and uses forward- and backpropagation to obtain the gradients respect to the model parameters (Lecun et al., 1998 §4).

2.1 Training with Static Oracles

With a static oracle, the training procedure computes a canonical reference series of transitions for each gold parse tree. It then runs the parser through this canonical sequence of transitions, while keeping track of the state representation \( \mathbf{p}_t \) at each step \( t \), as well as the distribution over transitions \( p(z_t \mid \mathbf{p}_t) \) which is predicted by the current classifier for the state representation. Once the end of the sentence is reached, the parameters are updated towards maximizing the likelihood of the reference transition sequence (Equation 2), which equates to maximizing the probability of the correct transition, \( p(z_{gt} \mid \mathbf{p}_t) \), at each state along the path.

2.2 Training with Dynamic Oracles

In the static oracle case, the parser is trained to predict the best transition to take at each parsing step, assuming all previous transitions were correct. Since the parser is likely to make mistakes at test time and encounter states it has not seen during training, this training criterion is problematic (Daumé III et al., 2009; Ross et al., 2011; Goldberg and Nivre, 2012; Goldberg and Nivre, 2013; inter alia). Instead, we would prefer to train the parser to behave optimally even after making a mistake (under the constraint that it cannot backtrack or fix any previous decision). We thus need to include in the training examples states that result from wrong parsing decisions, together with the optimal transitions to take in these states. To this end we reconsider which training examples to show, and what it means to behave optimally on these training examples. The framework of training with exploration using dynamic oracles suggested by Goldberg and Nivre (2012; 2013) provides answers to these questions. While the application of dynamic oracle training is relatively straightforward, some adaptations were needed to accommodate the probabilistic training objective. These adaptations mostly follow Goldberg (2013).

Dynamic Oracles. A dynamic oracle is the component that, given a gold parse tree, provides the optimal set of possible actions to take for any valid parser state. In contrast to static oracles that derive a canonical state sequence for each gold parse tree and say nothing about states that deviate from this canonical path, the dynamic oracle is well defined for states that result from parsing mistakes, and they may produce more than a single gold action for a given state. Under the dynamic oracle framework, an action is said to be optimal for a state if the best tree that can be reached after taking the action is no worse (in terms of accuracy with respect to the gold tree) than the best tree that could be reached prior to taking that action.

Goldberg and Nivre (2013) define the arc-decomposition property of transition systems, and show how to derive efficient dynamic oracles for transition systems that are arc-decomposable.

\[ ^2 \text{Specifically: for every parser configuration } p \text{ and group of } \]
fortunately, the arc-standard transition system does
not have this property. While it is possible to com-
pute dynamic oracles for the arc-standard system
(Goldberg et al., 2014), the computation relies on a
dynamic programming algorithm which is poly-
nomial in the length of the stack. As the dynamic or-
acle has to be queried for each parser state seen during
training, the use of this dynamic oracle will make
the training runtime several times longer. We chose
instead to switch to the arc-hybrid transition sys-
tem (Kuhlmann et al., 2011), which is very similar
to the arc-standard system but is arc-decomposable
and hence admits an efficient \( O(1) \) dynamic oracle,
resulting in only negligible increase to training run-
time. We implemented the dynamic oracle to the
arc-hybrid system as described by Goldberg (2013).

Training with Exploration. In order to expose
the parser to configurations that are likely to result
from incorrect parsing decisions, we make use of the
probabilistic nature of the classifier. During training,
instead of following the gold action, we sample the
next transition according to the output distribution
the classifier assigns to the current configuration.
Another option, taken by Goldberg and Nivre, is to
follow the one-best action predicted by the classifier.
However, initial experiments showed that the one-
best approach did not work well. Because the neural
network classifier becomes accurate early on in the
training process, the one-best action is likely to be
correct, and the parser is then exposed to very few
error states in its training process. By sampling from
the predicted distribution, we are effectively increas-
ing the chance of straying from the gold path during
training, while still focusing on mistakes that receive
relatively high parser scores. We believe further for-
mal analysis of this method will reveal connections
to reinforcement learning and, perhaps, other meth-
ods for learning complex policies.

Taking this idea further, we could increase the
number of error-states observed in the training pro-
cess by changing the sampling distribution so as
to bias it toward more low-probability states. We
do this by raising each probability to the power of
\( \alpha \) \((0 < \alpha \leq 1) \) and re-normalizing. This trans-
f ormation keeps the relative ordering of the events,
while shifting probability mass towards less frequent
events. As we show below, this turns out to be very
beneficial for the configurations that make use of
external embeddings. Indeed, these configurations
achieve high accuracies and sharp class distributions
early on in the training process.

The parser is trained to maximize the likelihood of
a correct action \( z_g \) at each parsing state \( p_t \) according
to Equation 1. When using the dynamic oracle, a
state \( p_t \) may admit multiple correct actions \( z_g =
\{ z_{g_1}, \ldots, z_{g_k} \} \). Our objective in such cases is the
marginal likelihood of all correct actions:
\begin{equation}
p(z_g | p_t) = \sum_{z_{g_1} \in z_g} p(z_{g_1} | p_t).
\end{equation}

3 Experiments

Following the same settings of Chen and Manning
(2014) and Dyer et al. (2015) we report results in
the English PTB and Chinese CTB-5. Table 1 shows
the results of the parser in its different configura-
tions. The table also shows the best result obtained
with the static oracle (obtained by rerunning Dyer et
al. parser) for the sake of comparison between static
and dynamic training strategies.

| Method                        | English | Chinese |
|-------------------------------|---------|---------|
| Arc-standard (Dyer et al.)    | 92.40   | 85.48   |
| Arc-hybrid (static)          | 92.08   | 85.66   |
| Arc-hybrid (dynamic)         | 92.66   | 86.07   |
| Arc-hybrid (dyn., \( \alpha = 0.75 \)) | 92.73   | 86.13   |
| + pre-training:              |         |         |
| Arc-standard (Dyer et al.)    | 93.04   | 86.85   |
| Arc-hybrid (static)          | 92.78   | 86.94   |
| Arc-hybrid (dynamic)         | 93.15   | 87.05   |
| Arc-hybrid (dyn., \( \alpha = 0.75 \)) | 93.56   | 87.65   |

Table 1: Dependency parsing: English (SD) and Chinese.

The score achieved by the dynamic oracle for
English is 93.56 UAS. This is remarkable given
that the parser uses a completely greedy search
procedure. Moreover, the Chinese score estab-
lishes the state-of-the-art, using the same settings as
Chen and Manning (2014).

\[ \text{A similar objective was used by Riezler et al. (2000), Char-
niak and Johnson (2005) and Goldberg (2013) in the context of}
\text{log-linear probabilistic models.} \]

\[ \text{The results on the development sets are similar and only}
\text{used for optimization and validation.} \]
Table 2: Dependency parsing results. The dynamic oracle uses $\alpha = 0.75$ (selected on English; see Table 1). PP refers to pseudo-projective parsing. Y’15 and A’16 are beam = 1 parsers from Yazdani and Henderson (2015) and Andor et al. (2016), respectively. A’16-beam is the parser with beam larger than 1 by Andor et al. (2016). Bold numbers indicate the best results among the greedy parsers.

| Method                  | Catalan UAS | Catalan LAS | Chinese UAS | Chinese LAS | Czech UAS | Czech LAS | English UAS | English LAS | German UAS | German LAS | Japanese UAS | Japanese LAS | Spanish UAS | Spanish LAS |
|-------------------------|-------------|------------|-------------|-------------|-----------|-----------|-------------|-------------|-------------|-------------|----------------|--------------|-------------|--------------|
| Arc-standard, static + PP| 89.60       | 85.45      | 79.68       | 75.08       | 77.96     | 71.06     | 91.12       | 88.69       | 88.09       | 85.24       | 93.10          | 92.28        | 90.08       | 85.00        |
| + pre-training          | –           | –          | 82.45       | 78.55       | –         | –         | 91.59       | 89.15       | 85.66       | 86.15       | –               | –            | 90.76       | 87.48        |
| Arc-hybrid, dyn. + PP   | 90.45       | 86.38      | 80.74       | 76.52       | 85.68     | 79.38     | 91.62       | 89.23       | 89.80       | 87.29       | 93.47          | 92.70        | 89.53       | 85.69        |
| + pre-training          | –           | –          | 83.54       | 79.66       | –         | –         | 92.22       | 89.87       | 90.34       | 88.17       | –               | –            | 91.09       | 87.95        |
| Y’15                    | 91.24       | 88.21      | 81.29       | 77.29       | 85.78     | 80.63     | 91.44       | 89.29       | 89.12       | 86.95       | 93.71          | 92.85        | 91.01       | 88.14        |
| A’16 + pre-training     | 92.67       | 89.83      | 84.72       | 80.85       | 88.94     | 84.56     | 93.22       | 91.23       | 90.91       | 89.15       | 93.65          | 92.84        | 92.62       | 89.95        |

The error-exploring dynamic-oracle training always improves over static oracle training controlling for the transition system, but the arc-hybrid system slightly under-performs the arc-standard system when trained with static oracle. Flattening the sampling distribution ($\alpha = 0.75$) is especially beneficial when training with pretrained word embeddings.

In order to be able to compare with similar greedy parsers (Yazdani and Henderson, 2015; Andor et al., 2016), we report the performance of the parser on the multilingual treebanks of the CoNLL 2009 shared task (Hajić et al., 2009). Since some of the treebanks contain nonprojective sentences and arc-hybrid does not allow nonprojective trees, we use the pseudo-projective approach (Nivre and Nilsson, 2005). We used predicted part-of-speech tags provided by the CoNLL 2009 shared task organizers. We also include results with pretrained word embeddings for English, Chinese, German, and Spanish following the same training setup as Dyer et al. (2015); for English and Chinese we used the same pretrained word embeddings as in Table 1 for German we used the monolingual training data from the WMT 2015 dataset and for Spanish we used the Spanish Gigaword version 3. See Table 2.

### 4 Related Work

Training greedy parsers on non-gold outcomes, facilitated by dynamic oracles, has been explored by several researchers in different ways (Goldberg and Nivre, 2012; Goldberg and Nivre, 2013; Goldberg and Nivre, 2014; Honnibal et al., 2013; Honnibal and Johnson, 2014).

We report the performance of these parsers in the most comparable setup, that is, with beam size 1 or greedy search.

Gómez-Rodríguez et al., 2014; Björkelund and Nivre, 2015; Tokgoz and Eryiğit, 2015; Gómez-Rodríguez and Fernández-González, 2015; Vaswani and Sága, 2016). More generally, training greedy search systems by paying attention to the expected classifier behavior during test time has been explored under the imitation learning and learning-to-search frameworks (Abbeel and Ng, 2004; Daumé III and Marcu, 2005; Vlachos, 2012; He et al., 2012; Daumé III et al., 2009; Ross et al., 2011; Chang et al., 2015).

Directly modeling the probability of making a mistake has also been explored for parsing (Yazdani and Henderson, 2015). Generally, the use of RNNs to conditionally predict actions in sequence given a history is spurring increased interest in training regimens that make the learned model more robust to test-time prediction errors. Solutions based on curriculum learning (Bengio et al., 2015), expected loss training (Shen et al., 2015), and reinforcement learning have been proposed (Ranzato et al., 2016). Finally, abandoning greedy search in favor of approximate global search offers an alternative solution to the problems with greedy search (Andor et al., 2016), and has been analyzed as well (Kulesza and Pereira, 2007; Pinley and Joachims, 2008), including for parsing (Martins et al., 2009).

### 5 Conclusions

Dyer et al. (2015) presented stack LSTMs and used them to implement a transition-based dependency parser. The parser uses a greedy learning strategy which potentially provides very high parsing
speed while still achieving state-of-the-art results. We have demonstrated that improvement by training the greedy parser on non-gold outcomes; dynamic oracles improve the stack LSTM parser, achieving 93.56 UAS for English, maintaining greedy search.

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