Transition-Based Dependency Parsing using Perceptron Learner

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Abstract

Syntactic parsing using dependency structures has become a standard technique in natural language processing with many different parsing models, in particular data-driven models that can be trained on syntactically annotated corpora. In this paper, we tackle transition-based dependency parsing using a Perceptron Learner. Our proposed model, which adds more relevant features to the Perceptron Learner, outperforms a baseline arc-standard parser. We beat the UAS of the MALT and LSTM parsers. We also give possible ways to address parsing of non-projective trees.

1 Introduction

Dependency parsing has been a hot topic in the NLP community for several decades. There have been seminal contributions with state-of-the-art performances in recent years. Transition-based methods have given competitive accuracies and efficiencies for dependency parsing. These parsers construct dependency trees by using a sequence of transition actions, such as SHIFT and REDUCE, over input sentences. Transition-based dependency parsing has gained considerable interest because it runs fast and performs accurately. Transition-based parsing gives complexities as low as \(O(n)\) and \(O(n^2)\) for projective and non-projective parsing, respectively (Nivre 2008). The complexity is lower for projective parsing because a parser can deterministically skip tokens violating projectivity, while this property is not assumed for non-projective parsing.

Greedy transition-based dependency parsing has been widely deployed because of its speed (Cer et al. 2010); however, state-of-the-art accuracies have been achieved by globally optimized parsers using beam search (Zhang and Clark 2008; Huang and Sagae 2010; Zhang and Nivre 2011; Bohnet and Nivre 2012). These approaches generate multiple transition sequences given a sentence, and pick one with the highest confidence. Coupled with dynamic programming, transition-based dependency parsing with beam search can be done very efficiently and gives significant improvement to parsing accuracy.

One downside of beam search is that it always uses a fixed size of beam even when a smaller size of beam is sufficient for good results. In our experiments, a greedy parser performs as accurately as a parser that uses beam search for about 64% of time. Thus, it is preferred if the beam size is not fixed but proportional to the number of low confidence predictions that a greedy parser makes, in which case, fewer transition sequences need to be explored to produce the same or similar parse output.

In this work, we only look at dependency parsing of projective trees, and propose ideas and directions to approach parsing of non-projective trees.

A dependency tree is a labeled directed tree \(T\) with

- a set \(V\) of nodes, labeled with words
- a set \(A\) of arcs, labeled with dependency types
- a linear precedence order \(<\) on \(V\)

It is basically a labeled directed graph \(G = (V_x, A)\) where

- \(V_x = 0, \ldots, n\) set of nodes. One for each position of a word \(x_i\) in the sentence plus a node 0 corresponding to a dummy \(ROOT\) variable.
- \(A \subset (V_x \times L \times V_x)\) is a set of labeled arcs of the form \((i, l, j)\) where \(i\) and \(j\) are nodes and \(l\) is the label from some set of labels \(L\). It should also be noted that the root node does not have an incoming edge, every node has at most one incoming arc and the graph is weakly connected.

There are two types of trees that satisfy these conditions:

- **Projective**: For every arc \((i, l, j)\), there is a directed path from \(i\) to every word \(k\) such that \(min(i, j) < k < max(i, j)\).
- **Non-projective**: This does not satisfy the constraints of a projective tree in that arcs can cross each other.

In these experiments, we try to parse only projective trees.
Non-projective tree

Figure 2: Example of a non-projective tree

Related Work

There has been several work done in the area of parsing in the NLP community. People have explored different kinds of parsing like phrase-structure parsing, dependency parsing etc. In particular, a lot of work has been done on dependency parsing and some of the seminal contributions which achieved state of the art performances are parsers like the arc-standard/arc-eager transition-based dependency parsing (Nivre 2004; 2008), using LSTMs (Dyer et al. 2015; Ballesteros, Dyer, and Smith 2015). There have also been work on graph-based dependency parsing (McDonald et al. 2005; Koo and Collins 2010; Carreras 2007; Eisner 1996).

Recently, several approaches involving natural language processing (Iyer et al. 2019b; Iyer and Sycara 2019; Iyer et al. 2019a; Iyer, Sycara, and Li 2017; Iyer and Rose 2019; Iyer et al. 2017; Iyer, Pei, and Sycara 2019; Iyer, Kohli, and Prabhumoye 2020), machine learning (Li et al. 2016a; Iyer et al. 2016; Honke, Iyer, and Mittal 2018; Iyer, Sharma, and Saradhi 2020; Li et al. 2016b), deep learning (Iyer et al. 2018; Li, Sycara, and Iyer 2018) and numerical optimizations (Radhakrishnan et al. 2016; Iyer and Tewfik 2012; Qian et al. 2014; Gupta et al. 2016; Radhakrishnan et al. 2018) have also been used in the visual and language domains.

In this work, we attempt to beat the MALT and LSTM parser by adding more features to the baseline parser using a perceptron learner.

Paper Organization

The paper is organized as follows. We formulate the problem and explain the approach in sections (2) and (3) respectively. The experimental results obtained along with their implications are discussed in section (4). In the section (5), we present ways of parsing non-projective trees. We finally draw conclusions and explore possibilities of future work in the last section (6) of the paper.

2 Problem Formulation

A transition-based dependency parser needs to predict the next parser action at nondeterministic choice points. The mechanism for doing this could be based on heuristics, but the most obvious and flexible solution is to use machine learning. We build upon an arc-standard parser using a perceptron learner incorporating advanced features. The feature templates and approaches taken are described in the next section.

| (a) | Features Templates $f(j, S)$ |
|-----|-------------------------------|
| 1   | $s_0.w \ s_0.t \ s_0.w \ o s_0.t$ |
| 2   | $s_1.w \ s_1.t \ s_0.w \ o s_1.t$ |
| 3   | $q_0.w \ q_0.t \ q_0.w \ o q_0.t$ |
| 4   | $s_1.t \ o s_1.w \ o s_0.t \ s_0.w \ o s_1.t$ |
| 5   | $s_0.w \ o q_0.t \ o q_0.t \ s_1.t \ o q_0.t \ s_0.w \ o q_0.t$ |

3 Technical Approach

In this work, we approach the transition-based dependency parsing problem using a Perceptron learner and build upon an arc-standard parser. We begin by implementing the functions to initialize the parser and execute transitions. We also implement the oracle, which would give correct transitions to take based on the gold-standard dataset, according to the Nivre’s arc-standard parsing algorithm. Several additional features were incorporated into the parser to enhance the perceptron learner (Huang and Sagae 2010). They are shown in Fig. 3. The baseline arc-standard parser gives a UAS of 52.81%.

In the feature template shown in Fig. 3, $s_i$ and $q_i$, represent the $i^{th}$ word of the stack and the buffer respectively. $s_i.w$ represents the POS tag of the $i^{th}$ word of the stack and $q_i.w$ represents the $i^{th}$ word token of the buffer. $s_i.lc$ and $s_i.rc$ represent the leftmost and rightmost children of $s_i$, respectively. In addition to these features, we incorporate some additional ones like

- $s_1.t \ o s_0.t \ o s_0.rc.w$
- $s_1.t \ o s_0.w \ o s_0.lc.w$
- $s_0.lc.t$
- $s_0.rc.t$
- $s_1.lc.t$
- $s_1.rc.t$

4 Results

The enhanced parser was tested on the development set as well as on the test set. The results are given in Table 1.

We see that the baseline arc-standard parser gives a UAS of 52.81% on the development whereas our model with a perceptron learner is able to give 82.79%. As we can see, we have obtained a significant improvement over the baseline with the added features.
| Model     | Development Set |
|-----------|-----------------|
| Baseline  | 52.81           |
| Enhanced  | 82.79           |

Table 1: Experimental Results obtained

5 Non-Projective Parsing

We had discussed about non-projective parsing in 1 and it is worth noting that the arc-standard parsing algorithm does not apply to non-projective trees. Several modifications and approaches have thus been proposed to address this limitation. Some of them are listed here:

- Algorithms for non-projective dependency parsing:
  - Constraint Satisfaction Methods (Foth, Daum, and Menzel 2004)
  - McDonald’s spanning tree algorithm (McDonald et al. 2005)
  - Covington’s algorithm (Nivre 2006)
- Post-processing of projective dependency graphs:
  - Pseudo-projective parsing (Nivre and Nilsson 2005)
  - Corrective modeling (Hall and Novák 2005)
  - Approximate non-projective parsing (McDonald and Pereira 2006)

Here, we look at two approaches: introducing a swap function in the arc-standard algorithm and also pseudo-projective parsing.

1. In the non-projective parsing algorithm proposed by Nivre, the algorithm constructs arcs only between adjacent words but can parse arbitrary non-projective trees by swapping the order of the words in the input (Nivre 2009). Basically a swapping operation was added to the existing arc-standard functions. The new set of functions are:

   - **LEFT-ARC:** $((σ[i], j), B, A) \Rightarrow ((σ[j], B, A ∪ (j, l, i))$, $i \neq 0$
   - **RIGHT-ARC:** $((σ[i], j), B, A) \Rightarrow ((σ[i], B, A ∪ (i, l, j))$
   - **SHIFT:** $σ, [i|β], A) \Rightarrow ((σ[i], β, A)$
   - **SWAP:** $((σ[i], j), [β], A) \Rightarrow ((σ[j], [i|β], A)$

It is important to note that the SWAP operation is permissible only when the two nodes on the top of the stack are in the original word order, which prevents the same two nodes from being swapped more than once, and when the leftmost node $i$ is different from the root node 0. This works for non-projective trees because any input can be sorted using SHIFT and SWAP, and any projective tree can be built using LEFT-ARC, RIGHT-ARC and SHIFT. Thus, by changing the word order using SWAP, we address the non-projective issue. The oracle is modified accordingly to accommodate the swap before the shift: $\text{elseif } (σ[i] > σ[0]), \text{then } \rightarrow \text{SWAP.}$ Here, $>$ refers to the inorder traversal linear order.

2. In Pseudo-projective parsing (Nivre and Nilsson 2005), the original non-projective tree is transformed to a projective tree. It is called psuedo because the modified tree is not the original tree. Here, each non-projective arc $(i, l, j)$ is the original tree replaced by $(k, l, j)$ such that $k$ is the closest ancestor of $i$ that does not violate the projectivity constraints. After all the computation is done on this, we can de-pseudo-projectivize the tree using some heuristic post-processing technique, the output of which will be a non-projective tree.

6 Conclusions and Future work

In this paper, we have implemented a working transition-based dependency parser using a perceptron learner with a lot of additional features. We have shown significant improvements over a baseline arc-standard parser. Other classifier methods like SVM can be explored and we can identify additional features that can better train the classifier.
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