A Minimal Span-Based Neural Constituency Parser

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Outline

1. Introduction
2. Background
3. Model
4. Algorithms
5. Training Details
6. Experiments
7. Conclusion
Intro: Overview

This paper:

- constituency parsing
- a novel greedy top-down inference algorithm
- independent scoring for label and span

The goal is to preserve the basic algorithmic properties of span-oriented (rather than transition-oriented) parse representations, while exploring the extent to which neural representational machinery can replace the additional structure required by existing chart parsers.
Intro: Penn Treebank

- The first publicly available syntactically annotated corpus
- Standard data set for English parsers
- Manually annotated with phrase-structure trees
- 48 preterminals (tags):
  - 36 POS tags, 12 other symbols (punctuation etc.)
- 14 nonterminals: standard inventory (S, NP, VP,...)
- Dataset for this paper
Intro: Constituency Parsing
Intro: Span and Label

input \{ \\
\begin{array}{c}
\text{PRP} \\
\text{She} \\
\text{VBZ} \\
\text{enjoys} \\
\text{VBG} \\
\text{playing} \\
\text{NN} \\
\text{tennis} \\
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\end{array}\}

span(0, 5) represent the full sentence, with label S.
In machine learning, the **hinge loss** is a loss function used for training classifiers. The hinge loss is used for "maximum-margin" classification, most notably for support vector machines (SVMs).\[1\]
Background: Transition Based Parser

- Do not admit fast dynamic programs and require careful feature engineering to support exact search-based inference (Thang et al., 2015)
- Require complex training procedures to benefit from anything other than greedy decoding (Wiseman and Rush, 2016)
Background: Chart Parser

- Require additional works, e.g., pre-specification of a complete context-free grammar for generating output structures and initial pruning of the output space.
- Do not achieve results competitive with the best transition-based models.
Algorithm: Chart Parsing

The basic model, compatible with traditional chart-based dp algorithms.

\[
T := \{ (\ell_t, (i_t, j_t)) : t = 1, \ldots, |T| \},
\]

\[
s_{\text{tree}}(T) = \sum_{(\ell, (i,j)) \in T} [s_{\text{label}}(i, j, \ell) + s_{\text{span}}(i, j)].
\]

Use modified CKY recursion to find the tree with highest score. \(O(n^3)\).
Model: Span Representation

Figure 3: Word spans are modeled by differences in LSTM output. Here the span 3 eating fish 5 is represented by the vector differences \((f_5 - f_3)\) and \((b_5 - b_3)\). The forward difference corresponds to LSTM-Minus (Wang and Chang, 2016).
Model: Scoring Functions

\[ s_{\text{labels}}(i, j) = V_{\ell}g(W_{\ell}s_{ij} + b_{\ell}), \]

\[ s_{\text{span}}(i, j) = v_{s}^{\top}g(W_{s}s_{ij} + b_{s}), \]

\[ s_{\text{label}}(i, j, \ell) = [s_{\text{labels}}(i, j)]_{\ell}, \]
Algorithm: Chart Parsing

- base case: \[ s_{\text{best}}(i, i + 1) = \max_\ell \left[ s_{\text{label}}(i, i + 1, \ell) \right] \]
- score of the split \((i, k, j)\) as the sum of its subspan scores:
  \[ s_{\text{split}}(i, k, j) = s_{\text{span}}(i, k) + s_{\text{span}}(k, j). \]
  \[ \tilde{s}_{\text{split}}(i, k, j) = s_{\text{split}}(i, k, j) + s_{\text{best}}(i, k) + s_{\text{best}}(k, j) \]
- joint label and split decision:
  \[ s_{\text{best}}(i, j) = \max_{\ell, k} \left[ s_{\text{label}}(i, j, \ell) + \tilde{s}_{\text{split}}(i, k, j) \right] \]
  \[ s_{\text{best}}(i, j) = \max_\ell \left[ s_{\text{label}}(i, j, \ell) \right] + \max_k \left[ \tilde{s}_{\text{split}}(i, k, j) \right] \]
Algorithm: Chart Parsing

Finally, $s_{\text{best}}(0, 5)$.

e.g. $s_{\text{best}}(1, 4) : [(1, 2), (2, 4)]; [(1, 3), (3, 4)];$

$$= \max[s_{\text{label}}(1,4)] + \max[(s_{\text{best}}(1, 2)+s_{\text{best}}(2, 4)+s_{\text{span}}(1, 2)+s_{\text{span}}(2, 4)),$$
$$(s_{\text{best}}(1, 3)+s_{\text{best}}(3, 4)+s_{\text{span}}(1, 3)+s_{\text{span}}(3, 4))]$$
Algorithms: Top-Down Parsing

At a high level, given a span, we independently assign it a label and pick a split point, then repeat this process for the left and right subspans.

- base case: \( \hat{\ell} = \arg \max_{\ell} [s_{\text{label}}(i, i + 1, \ell)] \)

- label and split decision: \( (\hat{\ell}, \hat{k}) = \arg \max_{\ell,k} [s_{\text{label}}(i, j, \ell) + s_{\text{split}}(i, k, j)] \)
  
  \[
  \hat{\ell} = \arg \max_{\ell} [s_{\text{label}}(i, j, \ell)], \\
  \hat{k} = \arg \max_{k} [s_{\text{split}}(i, k, j)],
  \]
Algorithms: Top-Down Parsing

(a) Execution of the top-down parsing algorithm.

(b) Output parse tree.
Training: Loss Functions

For a span \((i, j)\) occurring in the gold tree, let \(l^*\) and \(k^*\) represent the correct label and split point, and let \(\hat{l}\) and \(\hat{k}\) be the predictions made by computing the maximizations

- Hinge loss for label:
  \[
  \max \left( 0, 1 - s_{\text{label}}(i, j, l^*) + s_{\text{label}}(i, j, \hat{l}) \right)
  \]

- Hinge loss for split:
  \[
  \max \left( 0, 1 - s_{\text{split}}(i, k^*, j) + s_{\text{split}}(i, \hat{k}, j) \right)
  \]
Training: Alternatives

- Top-Middle-Bottom Label Scoring
- Left and Right Span Scoring
- Span Concatenation Scoring
- Deep Biaffine Span Scoring
- Structured Label Loss
Training: Details

- Penn Treebank for English experiments, French Treebank from the SPMRL 2014 shared task for French experiments.
- A two-layer bidirectional LSTM for our base span features. Dropout with a ratio selected from {0.2, 0.3, 0.4} is applied to all non-recurrent connections of the LSTM.
- All parameters (including word and tag embeddings) are randomly initialized using Glorot initialization.
- Adam optimizer with its default settings.
- Implemented in C++ using the DyNet neural network library (Neubig et al., 2017).
Evaluation Metric: F1 score

- The traditional F-measure or balanced F-score (F₁ score) is the harmonic mean of precision and recall

\[
F_1 = 2 \cdot \frac{1}{\frac{1}{\text{recall}}} + \frac{1}{\text{precision}} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}
\]
Results

### Final Parsing Results on Penn Treebank

<table>
<thead>
<tr>
<th>Parser</th>
<th>LR</th>
<th>LP</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Durrett and Klein (2015)</td>
<td>–</td>
<td>–</td>
<td>91.1</td>
</tr>
<tr>
<td>Vinyals et al. (2015)</td>
<td>–</td>
<td>–</td>
<td>88.3</td>
</tr>
<tr>
<td>Dyer et al. (2016)</td>
<td>–</td>
<td>–</td>
<td>89.8</td>
</tr>
<tr>
<td>Cross and Huang (2016)</td>
<td>90.5</td>
<td>92.1</td>
<td>91.3</td>
</tr>
<tr>
<td>Liu and Zhang (2016)</td>
<td>91.3</td>
<td>92.1</td>
<td>91.7</td>
</tr>
<tr>
<td>Best Chart Parser</td>
<td>90.63</td>
<td>92.98</td>
<td>91.79</td>
</tr>
<tr>
<td>Best Top-Down Parser</td>
<td>90.35</td>
<td>93.23</td>
<td>91.77</td>
</tr>
</tbody>
</table>

Processing one sentence at a time on a c4.4xlarge Amazon EC2 instance:
- Chart parser: 20.3 sens/s
- Top-down: 75.5 sens/s
Conclusion

Span-Based Neural Constituency Parser

- bi-LSTM for span representation
- dynamic programming chart-based decoding
- a greedy novel top-down inference procedure
- NN methods works