A Minimal Span-Based Neural Constituency Parser

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Outline

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Intro: Overview

This paper:

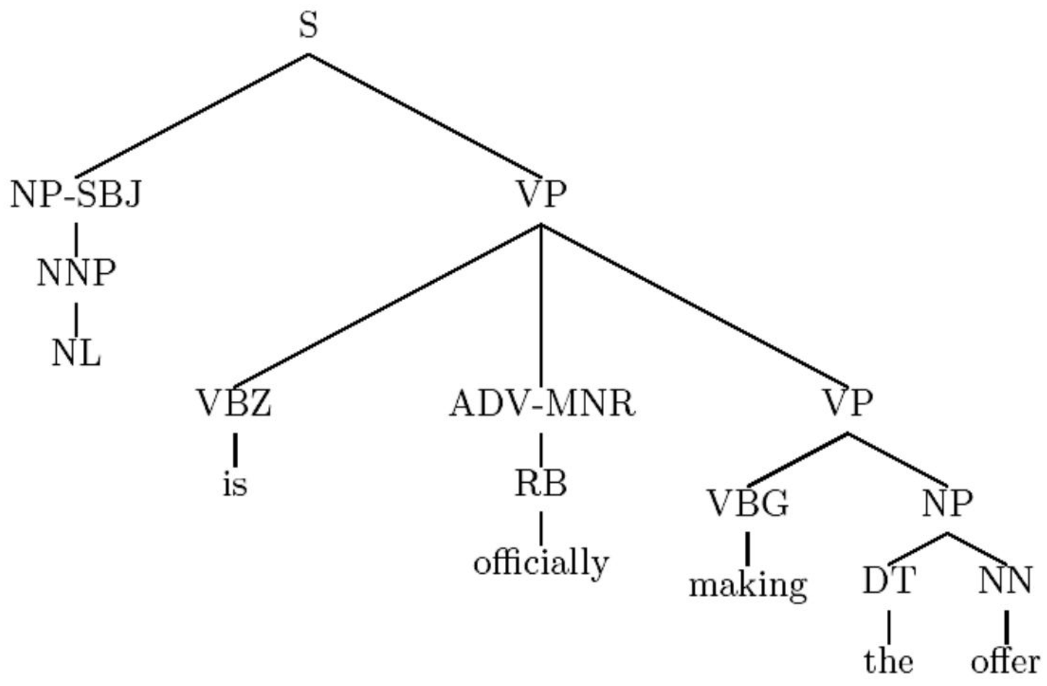
- constituency parsing
- a novel greedy top-down inference algorithm
- independent scoring for label and span

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.

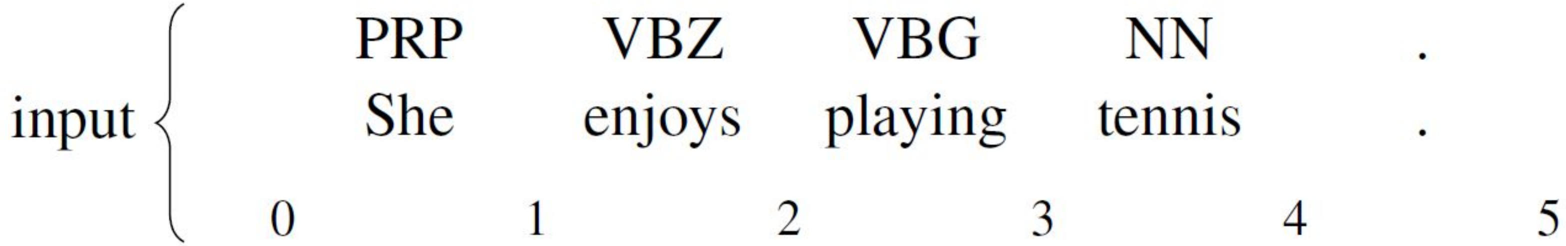
Intro: Penn Treebank

- 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



span(0, 5) represent the full sentence, with label S.

Intro: Hinge Loss

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.

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

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

Use modified CKY recursion to find the tree with highest score. O(n^3).

Model: Span Representation

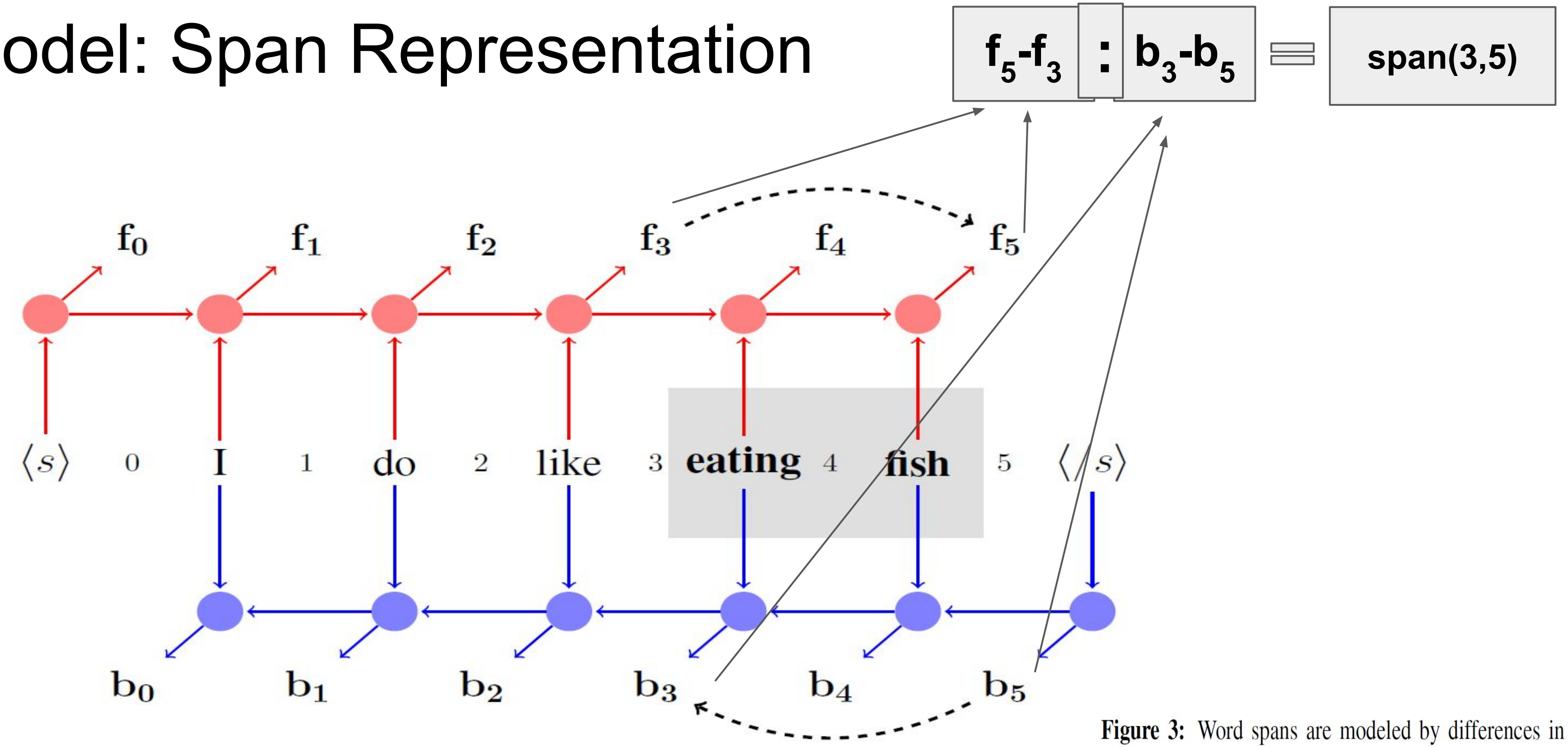


Figure 3: Word spans are modeled by differences in LSTM output. Here the span $_3$ *eating fish* $_5$ is represented by the vector differences ($f_5 - f_3$) and ($b_3 - b_5$). The forward difference corresponds to LSTM-Minus (Wang and Chang, 2016).

Model: Scoring Functions

$$s_{\text{labels}}(i, j) = \mathbf{V}_\ell g(\mathbf{W}_\ell \mathbf{s}_{ij} + \mathbf{b}_\ell),$$

$$s_{\text{span}}(i, j) = \mathbf{v}_s^\top g(\mathbf{W}_s \mathbf{s}_{ij} + \mathbf{b}_s),$$

$$s_{\text{label}}(i, j, \ell) = [s_{\text{labels}}(i, j)]_\ell,$$

Algorithm: Chart Parsing

- base case: $s_{\text{best}}(i, i+1) = \max_{\ell} [s_{\text{label}}(i, i+1, \ell)]$
- score of the split (i, k, j) as the sum of its subspan scores:

$$s_{\text{split}}(i, k, j) = s_{\text{span}}(i, k) + s_{\text{span}}(k, j).$$

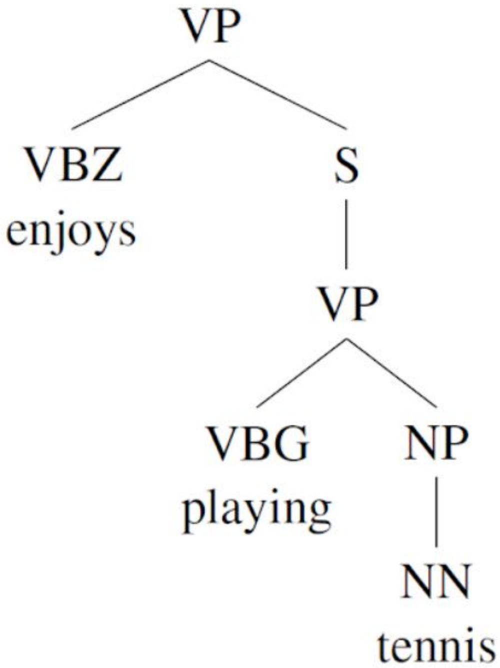
$$\tilde{s}_{\text{split}}(i, k, j) = s_{\text{split}}(i, k, j) + s_{\text{best}}(i, k) + s_{\text{best}}(k, j)$$

- joint label and split decision:

$$s_{\text{best}}(i, j) = \max_{\ell, k} [s_{\text{label}}(i, j, \ell) + \tilde{s}_{\text{split}}(i, k, j)]$$

$$s_{\text{best}}(i, j) = \max_{\ell} [s_{\text{label}}(i, j, \ell)] + \max_{k} [\tilde{s}_{\text{split}}(i, k, j)]$$

Algorithm: Chart Parsing



	PRP	VBZ	VBG	NN	.
	She	enjoys	playing	tennis	.
0	1	2	3	4	5

Finally, s_best(0, 5).

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

$$= \max[s_{label}(1,4)] + \max[(s_{best}(1, 2)+s_{best}(2, 4)+s_{span}(1, 2)+s_{span}(2, 4)),$$
$$(s_{best}(1, 3)+s_{best}(3, 4)+s_{span}(1, 3)+s_{span}(3, 4))]$$

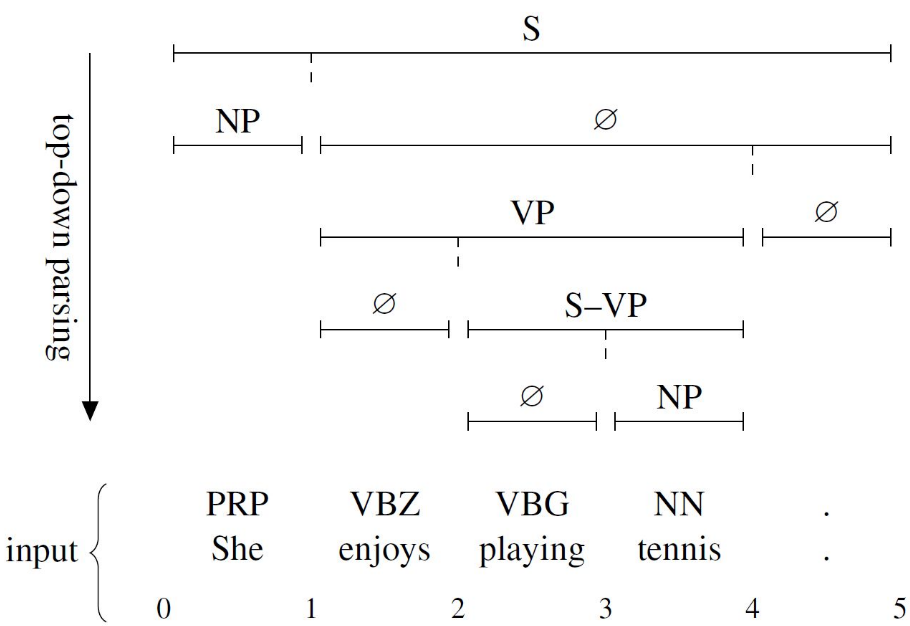
Algorithms: Top-Down Parsing

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.

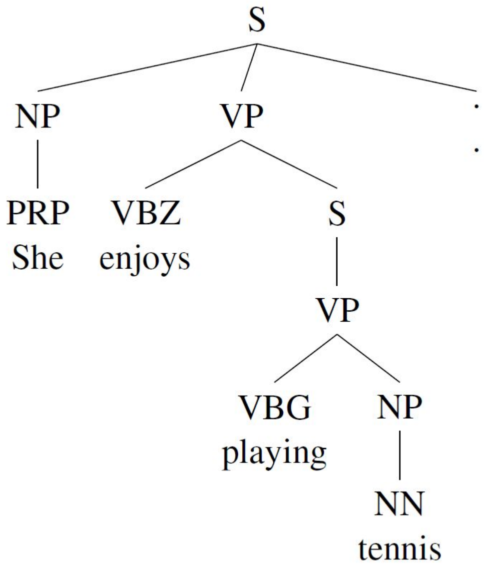
- base case: $\widehat{\ell} = \operatorname*{argmax}_{\ell} \left[s_{\text{label}}(i, i+1, \ell) \right]$
- label and split decision : $(\widehat{\ell}, \widehat{k}) = \operatorname*{argmax}_{\ell, k} \left[s_{\text{label}}(i, j, \ell) + s_{\text{split}}(i, k, j) \right]$

$$\widehat{\ell} = \operatorname*{argmax}_{\ell} \left[s_{\text{label}}(i, j, \ell) \right],$$
$$\widehat{k} = \operatorname*{argmax}_{k} \left[s_{\text{split}}(i, k, j) \right],$$

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 $\widehat{k}$ be the predictions made by computing the maximizations

- Hinge loss for label: $$\max\left(0, 1 - s_{\text{label}}(i, j, \ell^*) + s_{\text{label}}(i, j, \widehat{\ell})\right)$$
- Hinge loss for split: $$\max\left(0, 1 - s_{\text{split}}(i, k^*, j) + s_{\text{split}}(i, \widehat{k}, j)\right)$$

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 (**F_1 score**) is the harmonic mean of precision and recall

$$F_1 = 2 \cdot \frac{1}{\frac{1}{\mathrm{recall}} + \frac{1}{\mathrm{precision}}} = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}}$$

Results

Final Parsing Results on Penn Treebank

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

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