

CCG Parsing: Ambati et al., 2016

AUSTIN BLODGETT

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Review of Transition-based Parsing

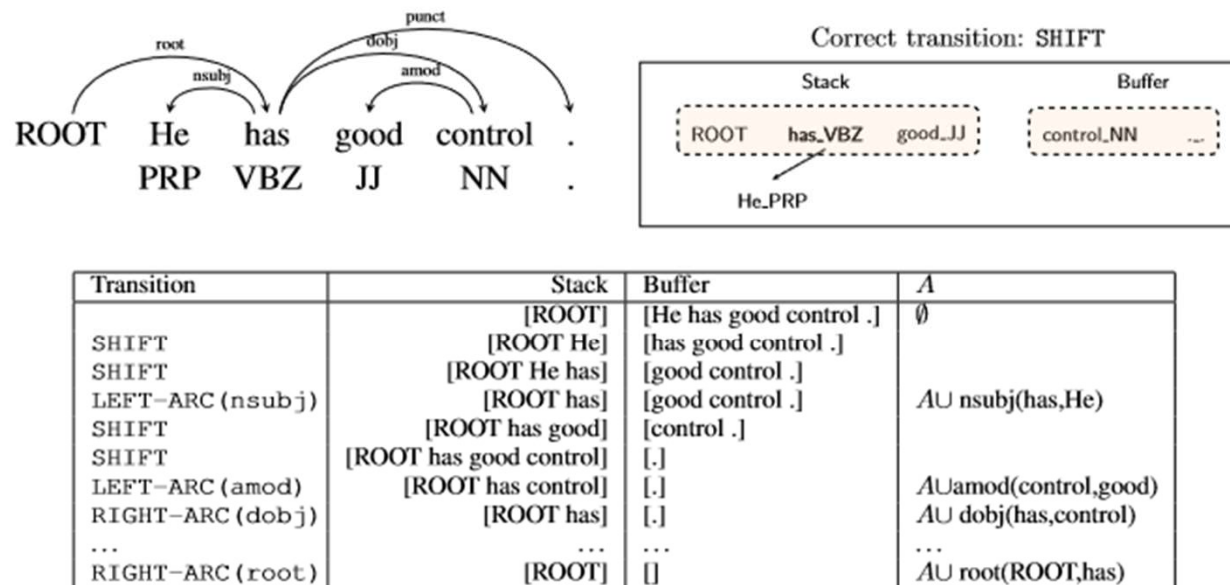
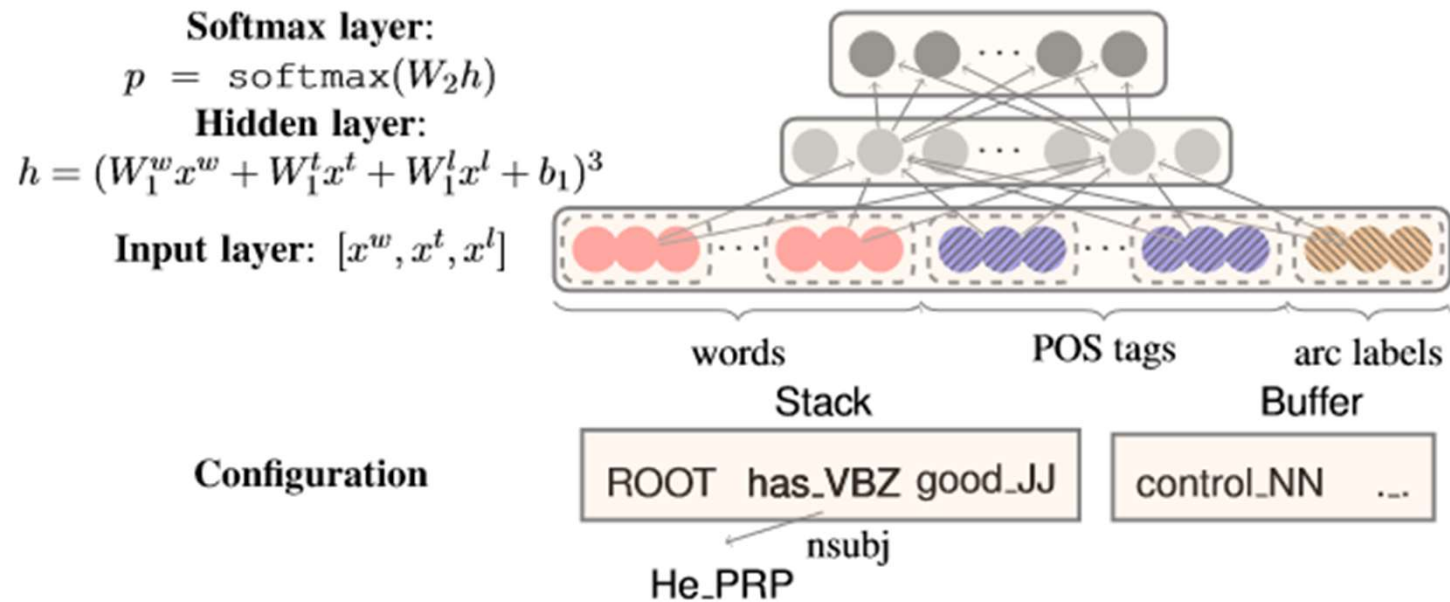


Figure 1: An example of transition-based dependency parsing. Above left: a desired dependency tree, above right: an intermediate configuration, bottom: a transition sequence of the arc-standard system.

Review of Transition-based Parsing

- **LEFT-ARC(l)**: adds an arc $s_1 \rightarrow s_2$ with label l and removes s_2 from the stack. Precondition: $|s| \geq 2$.
- **RIGHT-ARC(l)**: adds an arc $s_2 \rightarrow s_1$ with label l and removes s_1 from the stack. Precondition: $|s| \geq 2$.
- **SHIFT**: moves b_1 from the buffer to the stack. Precondition: $|b| \geq 1$.

Review of Transition-based Parsing



Ambati et al., 2016

How to parse CCG with Shift and Reduce?

New Transition Rules

- REDUCE-LEFT(cat): remove **s1** from the stack and tag constituent as **cat**
- REDUCE-RIGHT(cat): remove **s2** from the stack and tag constituent as **cat**
- REDUCE-UNARY(cat): remove **s1** (or s2?) from the stack and tag constituent as **cat**
- SHIFT: moves **b1** from the buffer to the stack

Ambati et al., 2016

Ambati et al.'s parser uses 2296 total Transitions:

- 340 REDUCE-LEFT(cat)
- 593 REDUCE-RIGHT(cat)
- 78 REDUCE-UNARY(cat)
- 1285 SHIFT

Ambati et al., 2016

Nodes to consider:

- a) top 4 nodes in the **stack**
- b) next 4 nodes in the **input**
- c) **left and right children** of the top 2 nodes in the stack

34 features:

- Word embeddings from (a-c)
- POS embeddings from (a-c)
- CCG tag embeddings from (a, b) + lexical heads of 2 nodes in the stack

Input layer = 34 x 50 (embedding size)

Ambati et al., 2016

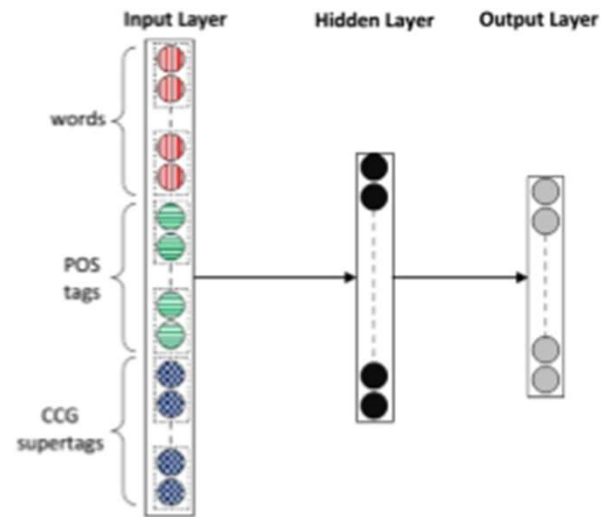


Figure 1: Our Neural Network Architecture (adapted from Chen and Manning (2014)).

Ambati et al., 2016

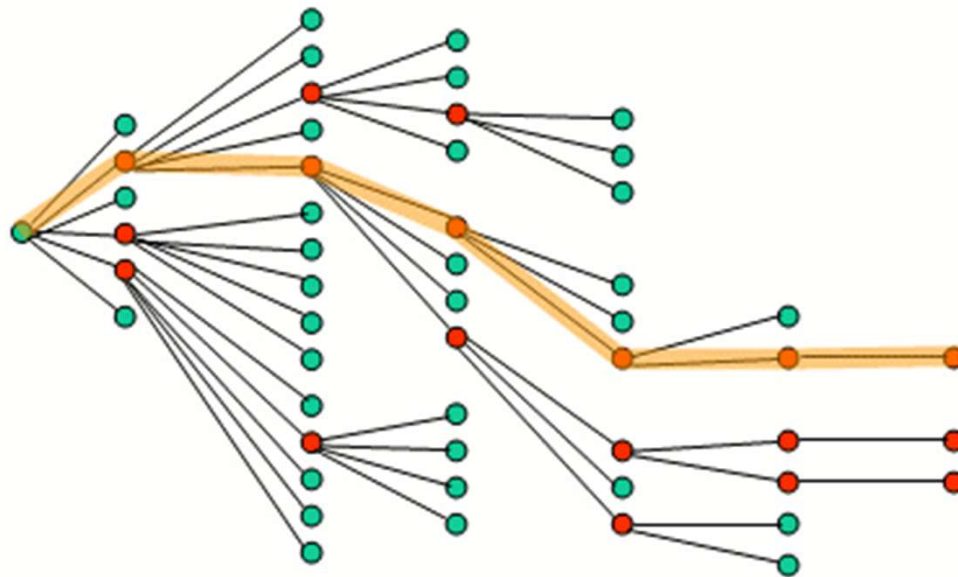
Greedy Search

<i>Model</i>	<i>Tagger</i>	<i>UF</i>	<i>LF</i>	<i>Cat.</i>
Z&C*	C&C	87.24	80.25	91.09
Our NNPar	C&C	89.38	82.65	91.72
Z&C*	NNT	87.00	79.78	90.52
Our NNPar	NNT	90.09	83.33	92.03

Table 1: Performance of greedy CCG parsers on CCGbank development data (Sec. 00).

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Beam Search



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Beam Search

<i>Model</i>	<i>Beam</i>	<i>UF</i>	<i>LF</i>	<i>Cat.</i>
Z&C*	1	87.28	80.78	91.44
Our NNPar	1	89.78	83.27	91.89
Z&C*	16	91.28	85.00	92.79
Our NNPar	16	91.14	84.44	92.22
Our Structured NNPar	16	91.95	85.57	92.86
Zhang and Clark (2011)	16	-	85.48	92.77
Xu et al. (2014)	128	-	86.00	92.75

Table 3: Results on CCGbank test data (Sec. 23).

Evaluation

1. Supertag Prediction (F1)
2. Unlabelled F1 (per constituent)
3. ✓ Labelled F1 (per constituent)
4. ✗ Exact Match

Other Approaches

1. LSTM CCG Parsing (Lewis et al. 2016)
2. A* CCG Parsing with a Supertag-factored Model (Lewis and Steedman, 2014)

CCG Leaderboard

C&C + RNN (Xu et al., 2015)

EasyCCG (Lewis and Steedman, 2014)

Leader (Lewis et al. 2016)

Model	P	R	F1
C&C	86.2	84.2	85.2
C&C + RNN	87.7	86.4	87.0
EASYCCG	83.7	83.0	83.3
Dependencies	86.5	85.8	86.1
LSTM	87.7	86.7	87.2
LSTM + Dependencies	88.2	87.3	87.8
LSTM + Tri-training	88.6	87.5	88.1
LSTM + Tri-training + Dependencies	88.2	87.3	87.8

Table 2: Labelled F1 for CCGbank dependencies on the CCGbank test set (Section 23).

CCG Leaderboard: Speed

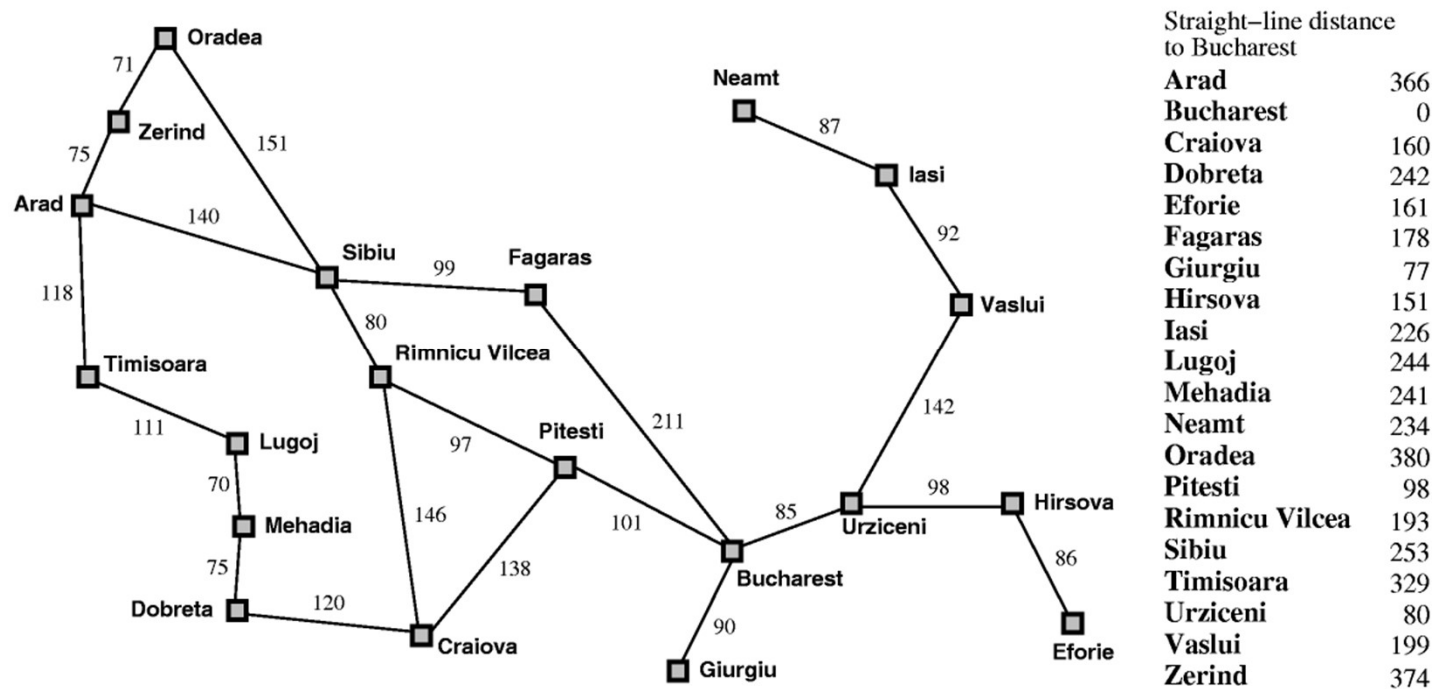
EasyCCG (Lewis and Steedman, 2014)

LSTM GPU (Lewis et al. 2016)

Parser	Sentences per second
SpaCy* ⁴	778
Berkeley GPU* (Hall et al., 2014)	687
Chen and Manning (2014)*	391
C&C	66
EASYCCG	606
LSTM	214
LSTM + Dependencies	58
LSTM GPU	2670

Table 4: Sentences parsed per second on our hardware. Parsers marked * use non-CCG formalisms but are the fastest available CPU and GPU parsers.

A* search (Lewis and Steedman, 2014)



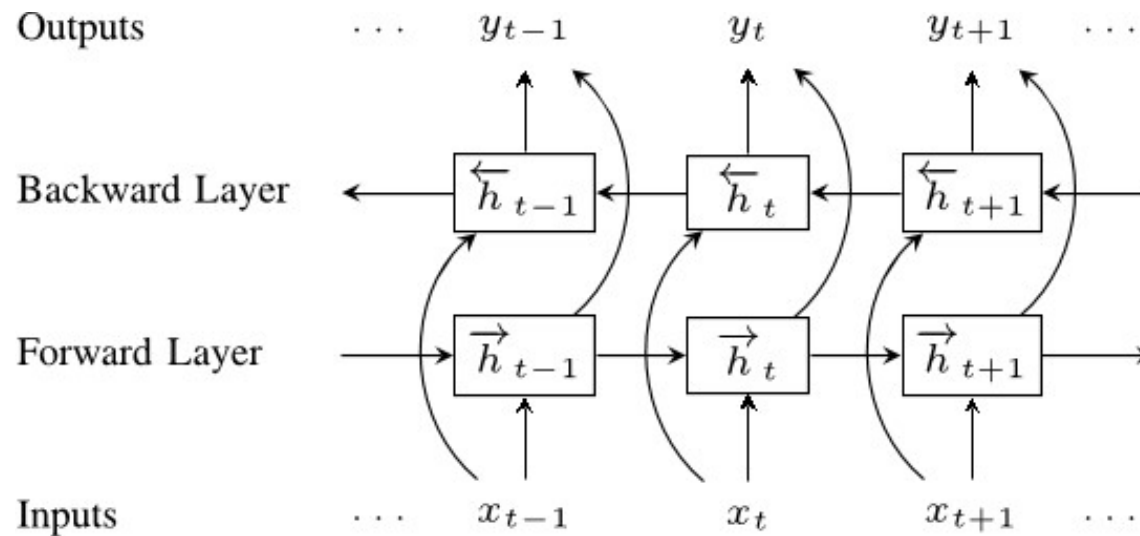
A* Parsing (Lewis and Steedman, 2014)

Choose next action x by minimizing:

- $f(x) = \text{dist}(\text{current}, x) + \text{dist}(x, \text{endpoint})$

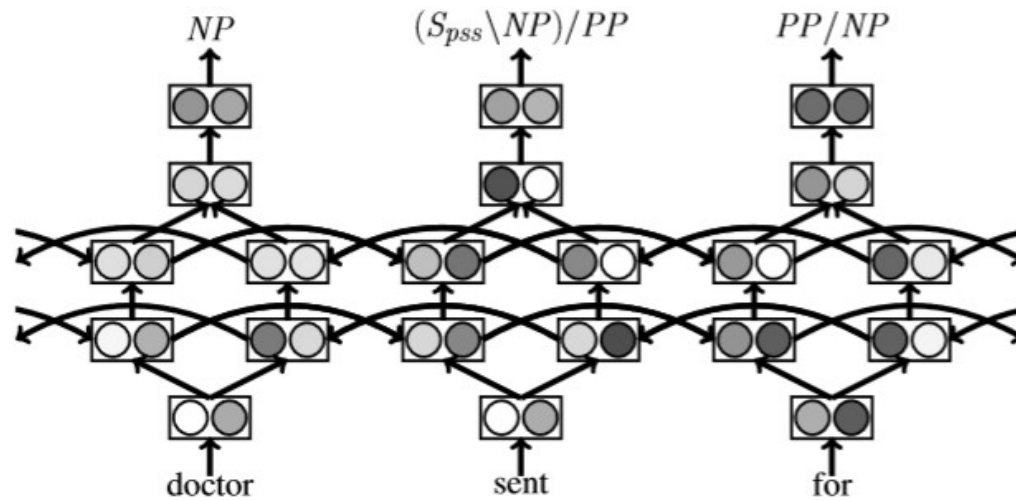
LSTM (Lewis et al. 2016)

Stacked BiLSTM Supertagger



LSTM (Lewis et al. 2016)

Contribution: What we need is a strict deterministic grammar and a great lexical tagger



Reflections

1. Computer Scientists like CCG for its syntax-semantics interface
 2. Much of effort spent on efficient search
 3. CCG Parsers tend to learn ad hoc combinators
 4. Graph-based approaches better, Transition-based approaches faster...
 5. Best Accuracy comes from smaller grammar
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