Faster Dependency Parsing, More Accurate Unsupervised Parsing

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Did Aristotle Have a Cellphone?

Leslie Valiant (2021)

Octopuses and Language

Bender and Koller (2020)

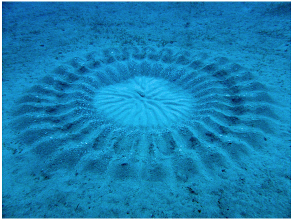
But... "There is no data like more data"

Maybe... There is no model like a bigger model?

This Talk

Part 1:
Show how to make dependency parsers *faster*

Part 2:
Show how to make unsupervised parsers *more accurate*



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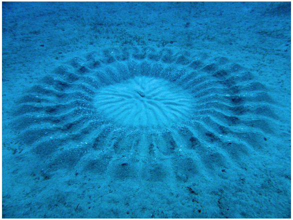
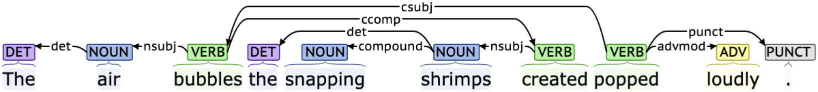


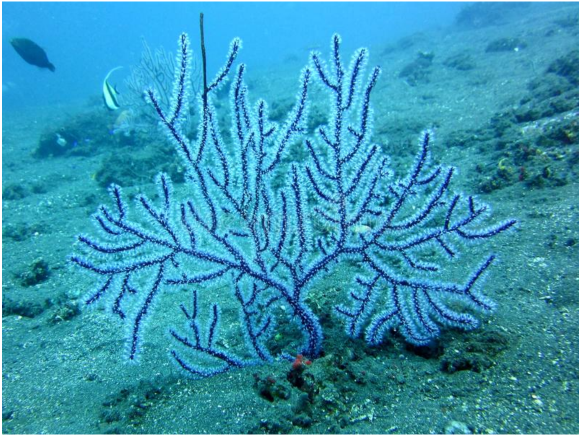
Dependency Parsing

From the Stanza parser:



- Parsers are not perfect yet!
- The Universal Dependencies Project aims at finding a common dependency formalism for many languages

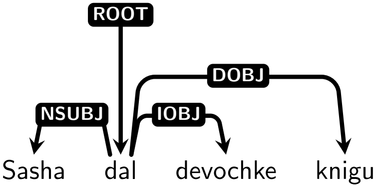
Why Dependency Parsing?



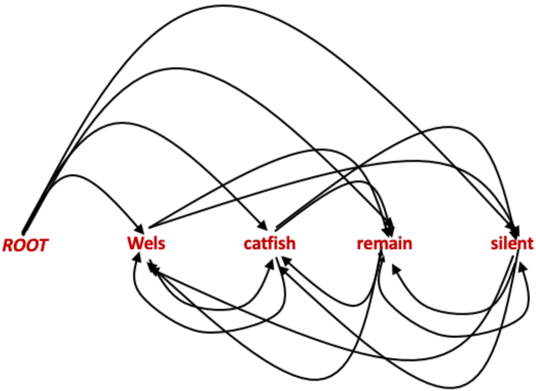
- It gives relations directly between words, no "deep" structure which is sometimes redundant
- This also makes it a better theory for free-word order languages
- Flexible at modelling non-projectivity

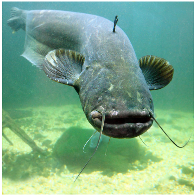
Side Note: Free Word Order Languages

- In languages with *free word order*, phrase structure (constituency) grammars don't make as much sense.
  - E.g., we would need both $\texttt{S} \rightarrow \texttt{NP VP}$ and $\texttt{S} \rightarrow \texttt{VP NP}$, etc. Not very informative about what's really going on.
- In contrast, the dependency relations stay constant (in Russian, "Sasha gave a book to the girl"):



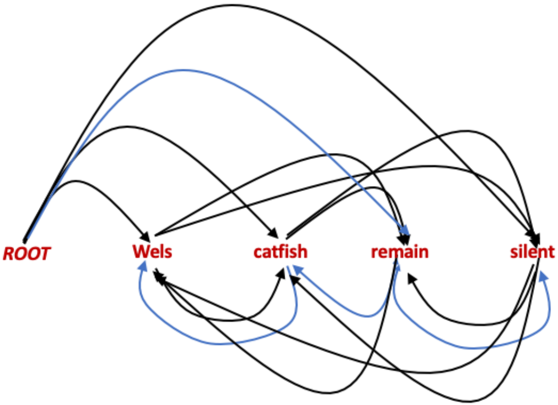
Graph Parsing for Dependency Parsing

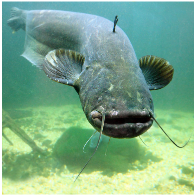




- STAGE 1: Start with a complete graph, all edges connected to each other with some weight

Graph Parsing for Dependency Parsing

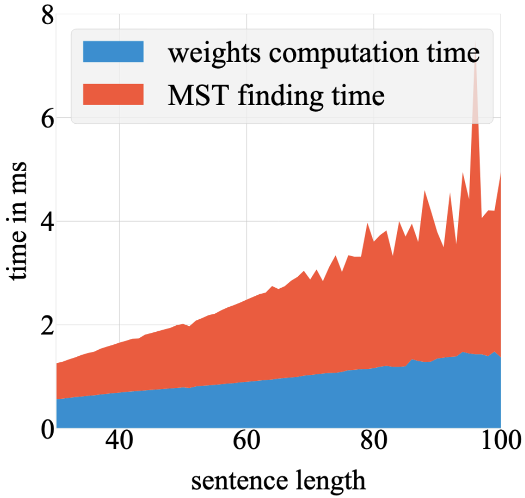




- STAGE 1: Start with a complete graph, all edges connected to each other with some weight
- STAGE 2: Run a maximum spanning tree algorithm to find the highest scoring tree

Where is Time Spent in Parsing?

Time spent on STAGE 1 and STAGE 2:



- Calculated from the Stanza parser
- Most time is spent on inference

The Root of a Problem

The Universal Dependency Project (Nivre et al., 2018) documentation states that (Zmigrod et al. 2020):

> *There should be just one node with the root dependency relation in every tree [...]*

`https://universaldependencies.org/u/dep/root.html`

We ask: **Can we optimally decode a dependency tree with a single-root constraint?** (Stanojević and Cohen, 2021)

Answer: **Yes**. Run asymptotically in quadratic time with an empirical low constant

Single-Root Dependency Parsing Algorithms

algorithm	appeared in	current implementation worst-case	claimed worst-case dense graph	average-case dense graph	claimed worst-case sparse graph
Gabow-Tarjan	Gabow & Tarjan (1984) Zmigrod et al. (2020)	$\mathcal{O}(n^2 \log n)$	$\mathcal{O}(n^2)$	$\mathcal{O}(n^2)$	$\mathcal{O}(m \log n)$
Naïve	mentioned in Zmigrod et al. (2020)	n/a	$\mathcal{O}(n^3)$	$\mathcal{O}(n^3)$	$\mathcal{O}(mn + n^2 \log n)$
Preselection	code of some parsers (undocumented)	$\mathcal{O}(n^3)$	$\mathcal{O}(n^3)$	$\mathcal{O}(n^2)$	$\mathcal{O}(mn + n^2 \log n)$
Reweighting	this work	$\mathcal{O}(n^2)$	$\mathcal{O}(n^2)$	$\mathcal{O}(n^2)$	$\mathcal{O}(m + n \log n)$

In the above, we might use as a subroutine an unconstrained parsing algorithm

For example: $\mathcal{O}(n^2)$, using our implementation of the Chu-Liu-Edmonds algorithm (CLE) based on data structures from Tarjan (1977)

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The Reweighting Algorithm

Consider the complete graph we start with our inference. If we subtract c from all edges $ROOT \to w_i$:

- We subtract from all trees the weight $k \cdot c$ where k is the number of $ROOT$ edges
- We do not change the weight order of trees with the same number of $ROOT$ edges
- We may change weight order of trees with different number of $ROOT$ edges

Question: Can we find c such that we make the best single-root tree come at the top compared to all other multiple root trees?

The Reweighting Algorithm

Question: Can we find c such that we make the best single-root tree come at the top compared to all other multiple root trees?

Answer: Yes! Choose $c^* = 1 + n(\max_e w(e) - \min_e w(e))$ where $w(e)$ is the weight of edge e in the complete graph

The Reweighting Algorithm:

- Subtract c^* from all $ROOT \rightarrow *$ edges in the initial complete graph
- Run an unconstrained tree inference algorithm on the new complete graph

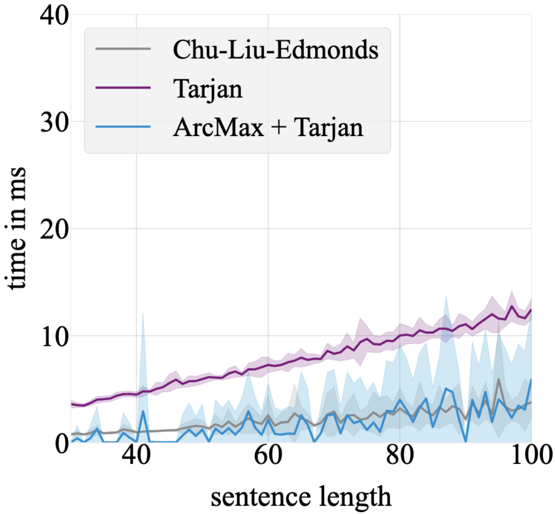
Side Note: the ArcMax Trick

Zhang et al. (2017) show that choosing for each word the highest scoring edge going into that word as parent often gives a valid tree

Use this as a trick: (a) check if this gives tree (this tree is optimal), if so, don't run any costly inference – we will go back to that!

Experiment 1A: Unconstrained Inference Speed

With trained weights (**unconstrained**):

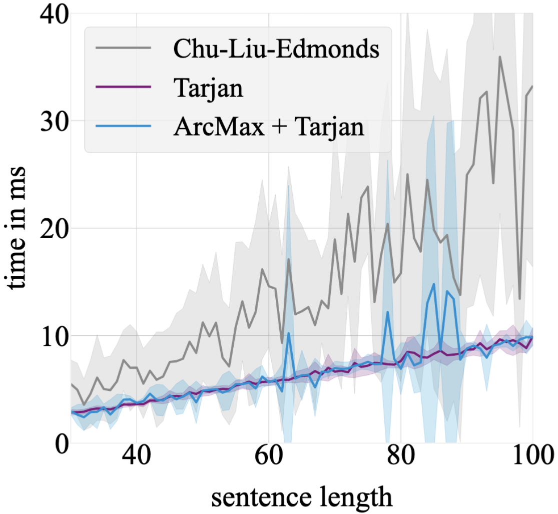


- The CLE algorithm includes an ArcMax-like step in the beginning (by design)

- Tarjan with ArcMax catches up...

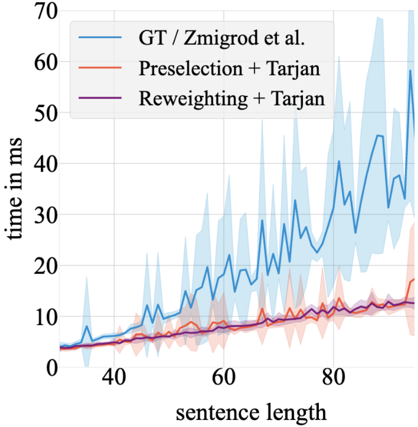
Experiment 1B: Unconstrained Inference Speed

With random weights (**unconstrained**):

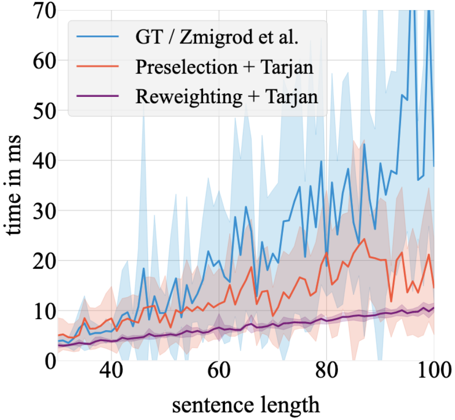


- ArcMax-like step no longer works, so Tarjan shines

Experiment 2: Single-Root Inference Speed without ArcMax

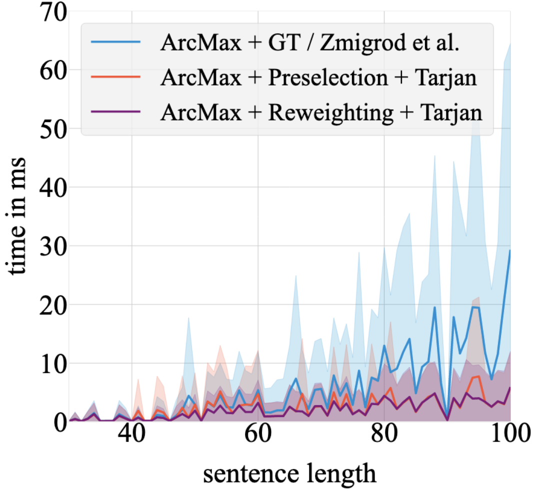


(a) Trained English input



(b) Random input

Experiment 3: Single-Root Inference Speed with ArcMax



- Random weights not shown - same as without ArcMax

Summary of Part 1

To get optimal complexity for single root, just use:

```
def reweighting(scores, mst_func):
    scores2 = np.where(np.isinf(scores), np.nan, scores)
    n = scores.shape[0]-1  # number of words
    scores[:, 0] -= 1 + n*(np.nanmax(scores2)-np.nanmin(scores2))
    return mst_func(scores)
```

Our recommendation for optimal single-root dependency parsing (regardless of learning): **ArcMax+Reweighting+Tarjan**

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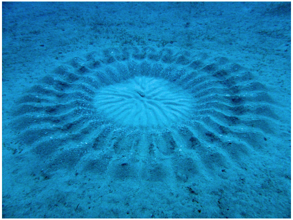
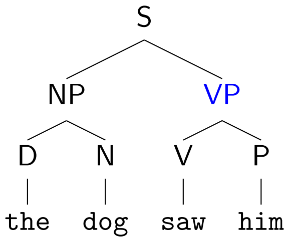


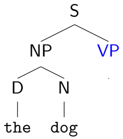
Unsupervised Parsing

L-PCFGs, the Supervised Case

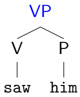
At node VP:



Outside tree $o =$



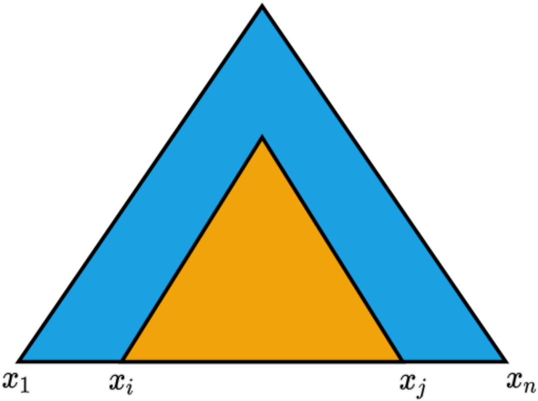
Inside tree $t =$



Conditionally independent given the label and the connecting nonterminal

$$p(o, t|\text{VP}) = p(o|\text{VP}) \times p(t|\text{VP})$$

Inside Outside Strings



- The yield of the orange part is "inside string"
- The yield of the blue part is "outside string"
- We will bootstrap a classifier to predict if a node dominates a pair of (inside,outside) strings

Co-training (Yarowsky, 1995; Blum and Mitchell, 1998)

Roughly! Repeats the following steps (given unlabeled data U and labeled data L):

- Train a classifier with one "view" on L
- Train a classifier with another "view" on L
- Take some (confident) predictions on U from both classifiers and add to L

Co-training works best when the two views are conditionally independent given the label

And In Our Case...

This leads to:

- Take all sentences, and break them all possible ways into inside/outside strings
- Get neural representations for each pair (i, o) as two "views"
- Take a subset of these L, and label them with some heuristics - the label is whether (i, o) has a node that connects them
- Do co-training

Weak Supervision

What would be the seed dataset to start the co-training process?

- All $(\textit{start}, \textit{end})$ spans for a given sentence have label 1 (are constituents)
- All $(\textit{start}, \textit{end} - i)$ for $i = 1, 2, ..., 6$ have label 0
- Another simple heuristic that relies on casing

How Do We Use These Labels?

Let

- $p_i(e)$ be the confidence of the classifier for an inside of span e
- $p_o(e)$ be the confidence of the classifier for an outside of span e

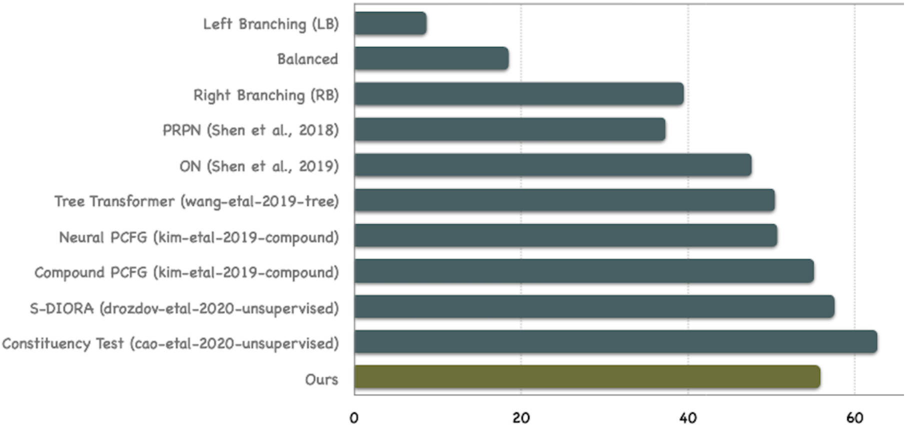
Then, for three different types of scores:

- *score*$(e) = p_i(e)$
- *score*$(e) = p_o(e)$
- *score*$(e) = p_i(e) \cdot p_o(e)$

find the tree $t^* = \arg\max_t \sum_{e \in t}$ *score*(e)

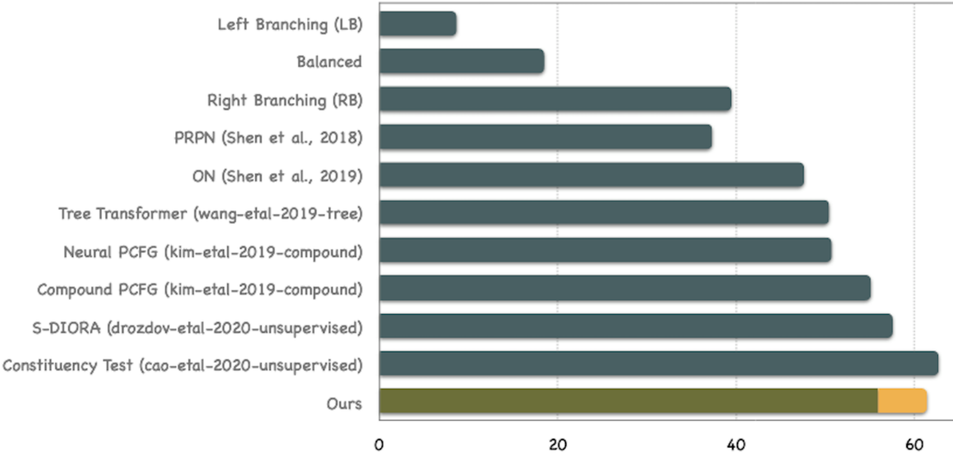
Also referred to as span decoding

Results: Penn Treebank (English)



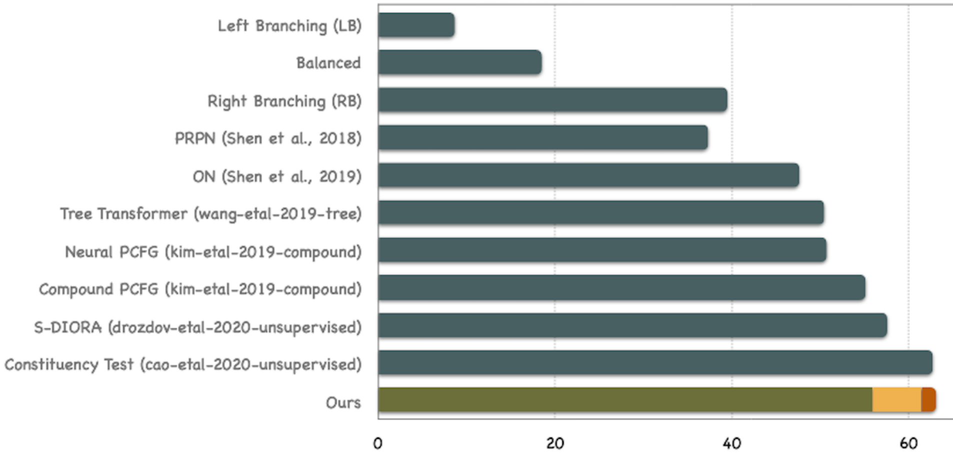
- Results with the inside score

Results: Penn Treebank (English)



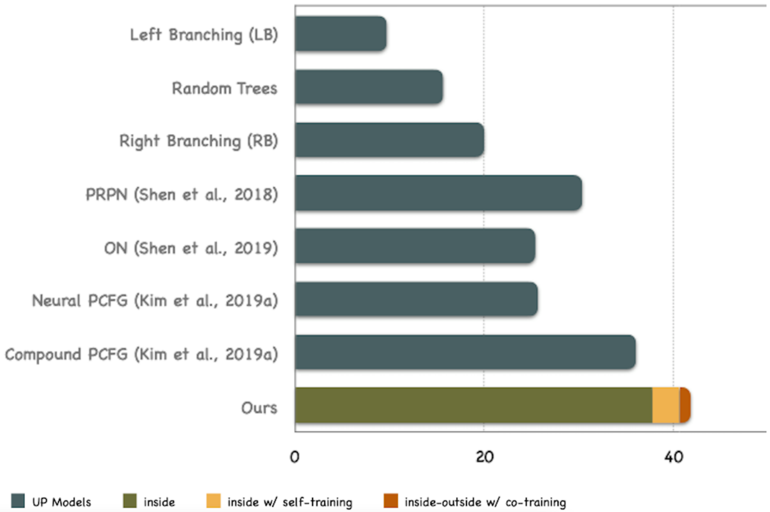
- Results with self-training of the inside score

Results: Penn Treebank (English)

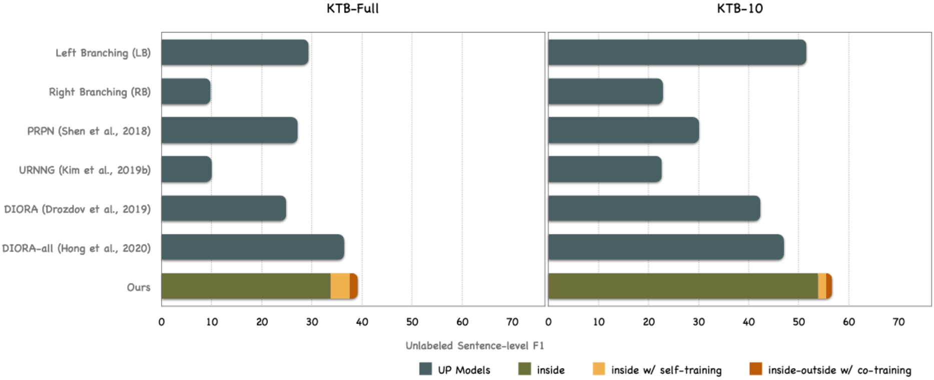


- Results with co-training for inside $\times$ outside scores

Results: Chinese Treebank



Results: Korean Treebank



Summary of Part 2

Unsupervised constituency parsing can be viewed as a co-training problem

See the paper for more examples, score functions and error analysis!

Conclusion

- Language is manifested through symbols. Computational systems in general are often symbolic in nature
- Its intermediate representation, however - can be continuous or symbolic
- Symbolic: interpretable; Continuous: have a gradient
- Both have their role. Both can co-exist

Thank You!

Any questions?

Collaborators

Milos Stanojević 

Nickil Maveli